The Sources of Fluctuations Within and Across Countries

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Abstract

This paper reviews the evidence on the sources of business cycles within and across countries and the implications for the importance of borders in business cycles. A simple econometric model is presented and applied to within–U.S. and cross–country data in order to provide a framework for interpreting the literature. Using these estimates as a benchmark, data issues, alternative models, and still other approaches to quantifying sources of comovement are surveyed. Overall, the evidence suggests three general conclusions. First, common shocks are less important in international fluctuations than in within–country fluctuations. Second, region–specific shocks account for a larger share of variation in international data than in within–country data. Finally, industry–specific shocks, measured accurately, are a smaller source of variation internationally than within countries. The paper then argues that lowering economic borders among nations through pacts like EMU should make the sources of international fluctuations look somewhat more like the sources of within–country fluctuations, although the effects are uncertain.

1. Introduction

Traditionally, business cycle research has focused on aggregate sources of national business cycles. For example, many studies have examined the role of monetary policy in the U.S. business cycle (recent examples include Christiano, Eichenbaum, and Evans (1996) and Cochrane (1998)). A recent literature has extended the traditional line of business cycle analysis in two directions. First, recognizing that a nation is comprised of many regions and industries, researchers have examined sources of fluctuations at both aggregate and disaggregate levels. Particularly, studies in this literature have considered the importance of national, region–specific, and industry–specific disturbances in quantity fluctuations experienced by a nation and propagation of those disturbances across regions and industries within a nation.[1] Second, researchers have examined the sources of international business cycles. Recent studies have analyzed the relative importance of common international, nation–specific, and industry–specific disturbances in quantity fluctuations experienced by different nations and propagation of those disturbances across nations and industries.

The newer literature on sources of fluctuations within and across countries provides evidence on the importance of borders in business cycle fluctuations. The world economy is divided by clearly defined borders that delineate *nations.* Each nation is further divided, to varying degrees, by clearly defined borders that delineate *regions.* To date, different nations generally determine monetary and fiscal policies independently and restrict migration. Regions within a nation typically determine local fiscal policies but are affected by national monetary and fiscal policy and allow free migration among regions. Industry mixes vary across nations as well as regions within a nation. Comparing the importance of different types of disturbances to regions with the importance of corresponding disturbances to nations around the world provides evidence on the importance of economic borders. For example, comparing the importance of national and state–specific shocks in the U.S. to the

[1] This paper surveys the evidence on within–country and cross–country *quantity* fluctuations, excluding studies, such as Engel and Rogers (1996), that examine *price* variation.

importance of common and nation–specific shocks to European nations provides some evidence on how the European Monetary Union (EMU) may affect the business cycles of member nations.

Drawing on the recent literature, this paper reviews the evidence on the sources of business cycles within and across countries and the implications for the importance of borders in business cycles.[2] A simple econometric model is presented and applied to within–U.S. and cross–country data in order to provide a basic framework for examining and interpreting the literature. After the model and benchmark results are presented, the paper discusses alternative data specifications and data issues, alternative model specifications, and still other approaches to quantifying sources of comovement. In addition to reviewing the various approaches used and results obtained in the literature, this study presents new evidence on how using alternative specifications affects results relative to the benchmark. The paper then discusses the implications of the overall evidence for the role of borders in business cycles, speculating on what the business cycle would look like in a world without economic borders. As pacts like EMU and the North American Free Trade Agreement (NAFTA) are extended, such a world may eventually be at hand.

Overall, the evidence reviewed in this paper yields three general conclusions on the sources of fluctuations within and across countries. First, common shocks are less important in international fluctuations than in within–country fluctuations. Second, region–specific shocks account for a larger share of variation in international data than in within–country data. Finally, industry–specific shocks, measured accurately, are a smaller source of variation internationally than within countries. This paper then argues that lowering economic borders among nations through pacts like EMU should make the sources of international fluctuations look somewhat more like the sources of within–country fluctuations. The effects are likely to be modest, however, given that the economic borders among nations will remain stronger than the borders among regions within a nation. Moreover,

[2] Focusing on the sources of regional fluctuations, this study abstracts from the numerous studies, such as Long and Plosser (1987) and Norrbin and Schlagenhauf (1991), that examine only industry fluctuations.

the qualitative effects are uncertain, because the structural forces behind the historical estimates of common, region–specific, and industry–specific shocks are not known.

Section 2 presents a simple econometric model used in this paper and in much of the literature to disentangle the sources of fluctuations. Section 3 presents results for a benchmark model fit to within–U.S. and cross–country data and reviews the results obtained by previous studies using essentially the same model. In section 4, some alternative data specifications and data issues are discussed. Sections 5 and 6 survey some variations on the benchmark model used in the literature. Section 7 reviews some other approaches to examining sources of comovement. Section 8 provides a broad summary of the literature and draws implications for the role of borders in business cycles. Section 9 concludes.

2. A Basic Model and Interpretations

While the literature on the sources of fluctuations within and across countries features a variety of specific models, many studies have used variants of a simple error model. Reduced to its essential elements — in particular, stripped of dynamics — this model takes the form

$$e_{r,i,t} = c_t + u_{r,t} + n_{i,t} + v_{r,i,t}. \tag{1}$$

According to this model, a shock $e_{r,i,t}$ to industry i in region r (for simplicity, "region" is used to refer to both a region within a nation and to a nation) reflects: a common (national for within–U.S. analysis or world for cross–country analysis) shock c_t; a region r–specific shock $u_{r,t}$; an industry i–specific shock $n_{i,t}$; and a shock idiosyncratic to industry i in region r.[3] Many studies, such as Altonji and Ham (1990), Norrbin and Schlagenhauf (1988, 1996), and Stockman (1988), estimate models having the basic form of (1). Others, such as Ghosh and Wolf (1997), can be viewed as implicitly or explicitly using (1) to interpret cross–region and cross–industry correlations.

[3] In this model, disaggregate shocks have aggregate effects only through what Altonji and Ham (1990) label the "collective impact." For example, the model allows the average level of industry–specific shocks in a given period to differ from zero and thereby affect the level of activity in a nation as a whole. The model does not capture Lilien's (1982) sectoral shifts effects, in which the cross–sector variance of the shocks at a point in time actually affects the level of aggregate activity.

Typically, the error model (1) is identified by assuming the common, region–specific, and industry–specific shocks to be mutually independent. Accordingly, a region–specific shock is just that: a shock $u_{r,t}$ to region r at time t does not affect any other region at time t and is uncorrelated with all other shocks. While some may view this formulation as overly restrictive, it in fact provides a useful benchmark estimate — a lower bound — of the importance of region–specific and industry–specific forces. Applied to regions within the U.S., for example, the model attributes all comovement among regions to the common and industry–specific components. If some of the observed regional comovement in fact stems from correlation among the region–specific shocks or from a shock to region r having contemporaneous effects on region s, the estimates will generally overstate the importance of the national component and understate the importance of the region shocks. Clark (1998) reports that augmenting an aggregated, within–U.S. model to allow separate shocks common to particular groups of regions reduces the estimated importance of the common national shock and raises the overall importance of region shocks.[4]

As discussed in studies such as Altonji and Ham (1990), Clark (1998), Norrbin and Schlagenhauf (1988, 1996), and Stockman (1988), the common, region–specific, and industry–specific shocks that drive business cycle variation in the model are generally viewed as having a variety of sources. In within–country analysis, the common shock captures the effects of innovations in aggregate (national) supply and demand, such as fiscal or monetary policy changes. Recent evidence suggests that, within the U.S., region–specific shocks may have several sources. Hooker and Knetter (1997) and Davis, et. al. (1997) find that changes in the regional distribution of national military spending have significant region–specific effects. The model developed by Samolyk (1989) and empirical evidence presented by Samolyk (1994) suggests regional heterogeneity in financial conditions to be an important mechanism for the generation of region–specific fluctuations. It is also possible to spec-

[4] Focusing on just two–digit industries, Horvath and Verbrugge (1997) allow a shock to industry i to have an immediate effect on any industry j which is directly linked by an input–output relationship. The Horvath and Verbrugge identification also produces a larger role for industry shocks than would an identification assuming the shock to i has no contemporaneous effect on j.

ulate that region–specific employment shocks may stem from changes in regional fiscal policy. In cross–country analysis, the common component reflects international developments such as oil price changes and common movements in nations' monetary and fiscal policies. In both within–country and cross–country analysis, the industry–specific shocks stem from changes in product demand, input prices, and productivity or technology.

Admittedly, however, interpretation of the shocks in the error model (1) is complicated by the absence of an accompanying economic model. The studies using specifications of the form (1) to examine sources of fluctuations generally do so without guidance from a concrete economic model. Certainly, though, not all studies in the literature have worked without guidance from theory. As discussed in more detail below, Bayoumi and Eichengreen (1993) and Chamie, et. al. (1994) examine the comovement of aggregate supply and demand shocks identified with variants of Blanchard and Quah's (1989) structural VAR. Ahmed, et. al. (1993) and Kwark (1996) assess comovement using a structural VAR based on a dynamic, stochastic, general equilibrium model featuring shocks to technology, labor supply, etc.

3. A Benchmark Specification and Results from that Specification

This section first presents a version of the basic model (1) that incorporates dynamics and a richer parameterization. Benchmark results from that specification are then presented. The section concludes by comparing the results to those from previous studies relying on essentially the same model.

3.1 The disaggregate VAR/factor model

The benchmark model, referred to henceforth as the *disaggregate VAR/factor model*, takes the essential form laid out by Altonji and Ham (1990) and Norrbin and Schlagenhauf (1988, 1996).[5] Let $X_{r,i,t}$, $X_{r,t}$, $X_{i,t}$, and X_t denote growth in, respectively: industry i in region r; region r; industry

[5] This paper refers to the model as a VAR because the dynamics are captured by weighted averages of lagged dependent variables. Norrbin and Schlagenhauf (1988, 1996), however, allow the common, region–specific, and industry–specific factors to follow autoregressive processes and view the model as fitting within the general index model class.

i; and either the U.S. overall or the world. The basic model equations are

$$X_{r,i,t} = \mu_{r,i} + \sum_{p=1}^{P} \alpha_{r,i,p} X_{t-p} + \sum_{p=1}^{P} \beta_{r,i,p} X_{r,t-p} + \sum_{p=1}^{P} \gamma_{r,i,p} X_{i,t-p} + e_{r,i,t} \tag{2}$$

$$e_{r,i,t} = \delta_{r,i} c_t + \theta_{r,i} u_{r,t} + \lambda_{r,i} n_{i,t} + v_{r,i,t}. \tag{3}$$

With R regions and I industries, the model includes RI equations of the form (2) and RI equations of the form (3).

The set of equations of the form (2) captures the dynamics of fluctuations with a restricted version of a VAR for the set of region–industry variables. The aggregate variables on the right side of (2) are constructed as fixed–weight averages of the region–industry variables, with weights corresponding to output or employment shares:

$$X_t = \sum_{r=1}^{R} \sum_{i=1}^{I} w_{r,i} X_{r,i,t}, \quad \sum_{r=1}^{R} \sum_{i=1}^{I} w_{r,i} = 1 \tag{4}$$

$$X_{r,t} = \sum_{i=1}^{I} a_{r,i} X_{r,i,t}, \quad \sum_{i=1}^{I} a_{r,i} = 1 \tag{5}$$

$$X_{i,t} = \sum_{r=1}^{R} b_{r,i} X_{r,i,t}, \quad \sum_{r=1}^{R} b_{r,i} = 1. \tag{6}$$

Letting Y_t denote the $RI \times 1$ vector of region–industry growth rates, the system of RI equations of the form (1) can then be written as a restricted VAR:

$$Y_t = \sum_{p=1}^{P} \Pi_p Y_{t-p} + e_t \tag{7}$$

$$\Pi_p = \alpha_p W_{RI} + \beta_p W_R + \gamma_p W_I. \tag{8}$$

α_p is an $RI \times 1$ vector of the α coefficients for lag p; β_p is an $RI \times R$ matrix containing the β coefficients for lag p; γ_p is an $RI \times I$ matrix containing the γ coefficients for lag p; W_{RI} is a $1 \times RI$ array of the $w_{r,i}$ weights; W_R is an $R \times RI$ matrix containing the $a_{r,i}$ weights; and W_I is an $I \times RI$ matrix containing the $b_{r,i}$ weights. The lag length P is set at 4 for quarterly data and 1 for annual data.

The error model (3) generalizes (1) by allowing unrestricted response coefficients on the common, region–specific, and industry–specific shocks. Identification, however, requires some scale restrictions. Accordingly, the variances of the structural shocks c_t, $u_{r,t}$ ($r = 1, \ldots, R$), and $n_{i,t}$ ($i = 1, \ldots, I$) are all normalized to 1. The $\phi_{r,i}$, $\theta_{r,i}$, and $\lambda_{r,i}$ coefficients are free parameters to be estimated.

The disaggregate VAR/factor model is estimated in a two–step procedure. In the first, the RI regressions of the form (2) are each estimated by OLS. In the second, the regression residuals are used in estimating the RI equations of the error model (3) by maximum likelihood (ML), as implemented with the EM algorithm, following Watson and Engle (1983) and Quah and Sargent (1993).[6] While computationally simple, this estimation procedure has an important drawback: calculating standard errors for the error model estimates is intractable.[7] In smaller models, standard errors can normally be estimated using the inverse of the outer product of the score vector from the EM estimates (see Ruud (1991)). In the disaggregate VAR/factor model, however, the number of error model parameters exceeds the number of observations, making the outer product singular. Accordingly, this study, like Norrbin and Schlagenhauf (1988, 1996), generally omits standard errors in presenting the disaggregate model results. However, to provide a rough sense of the sampling uncertainty, for one set of estimates — based on quarterly, within–U.S employment — Monte Carlo–generated standard errors are reported. The Monte Carlo data are generated using the fitted regression equations and normally–distributed errors with a covariance matrix equal to the fitted covariance matrix.[8] The procedure is only used for one model because the simulations

[6] The resulting estimates, however, are not in fact ML estimates. Because the regressors in (2) differ across equations, true ML would require estimating the model (2) and (3) jointly.

[7] While the EM algorithm is used in this analysis simply because it seems more tractable than the GMM approach used by Altonji and Ham (1990) and Krieger (1989), GMM estimation would permit the calculation of appropriate standard errors, subject to the assumption of normally distributed data.

[8] More specifically, time series of the vector of shocks $e_{r,i,t}$ are drawn from a normal distribution, with the covariance matrix set to that fitted from the sample estimates of (3). These shocks are then used in conjunction with the sample estimate of the restricted VAR (7) to generate 500 datasets of artificial time series. For each of those datasets, the disaggregate VAR/factor model is fit and the variance shares calculated. The reported standard errors are then standard deviations of the shares across the Monte Carlo estimates.

for a given model require roughly one week on a UNIX network.

In the interest of brevity, the results presented below are generally limited to the statistics of primary interest: shares of variance due to common, region–specific, industry–specific, and idiosyncratic shocks. Decompositions are reported for both innovation variances (1–step ahead forecast error variances) and for steady–state variances (infinite–step ahead forecast error variances). Following Altonji and Ham (1990) and Norrbin and Schlagenhauf (1988, 1996), steady–state variance shares are calculated using the fitted innovation variance matrix and the restricted VAR structure of the model. With the VAR rewritten in companion form, the steady–state variance is calculated as the 251–period ahead forecast error variance.

Variance decompositions are reported for two levels of aggregation: industries within regions ($X_{r,i,t}$) and aggregate regions ($X_{r,t}$). For brevity's sake, the region–industry decompositions are summarized by the averages of shares across all region–industry variables. The decomposition for the set of R aggregate regions is based on the fact that the $R \times 1$ vector of growth rates for the region aggregates, $X_{R,t}$, is given by $X_{R,t} = W_R Y_t$, where W_R and Y_t are defined as above. The k–step ahead forecast error variance for the set of region aggregates can then be calculated as $\mathrm{Var}(X_{R,t+k}|Y_t) = W_R \cdot \mathrm{Var}(Y_{t+k}|Y_t) \cdot W_R'$. If the disaggregate model were the true model, the k–step ahead aggregate variance calculated in this way would be the variance of the optimal forecast, which would be based on the disaggregate model.

Aggregation will naturally cause the sources of aggregate region variation to differ somewhat from the sources of region–industry variation. The variance for an aggregate region depends on not only the variances for industries within the region but also the covariances across the industries. While the variances for industries in a region ($\mathrm{Var}(X_{r,i,t})$) are driven by common, region–specific, industry–specific, and idiosyncratic shocks, covariances across the industries ($\mathrm{Cov}(X_{r,i,t}, X_{r,j,t})$) are driven by only common and region–specific disturbances. Accordingly, common and region–specific shocks will be more important in the covariances across industries ($\mathrm{Cov}(X_{r,i,t}, X_{r,j,t})$) than in the variances of industries within the region ($\text{Var}(X_{r,i,t})$). With the variance for an aggregate region depending on the variances and covariances of industries in the region, common and region–specific shocks will be more important to an aggregate region than to the typical industry within the region.

3.2 Data

As discussed in more detail in section 4, data availability sharply limits feasible model estimation. At the quarterly frequency, the only broad business cycle indicator available by industry within the U.S. is employment, while the only broad indicator available by industry across countries is industrial production. Accordingly, the disaggregate VAR/factor model is estimated using quarterly data on growth in: (1) employment in eight SIC one–digit industries in the eight aggregate U.S. regions defined by the Bureau of Economic Analysis (hereafter referred to as the BEA regions); and (2) industrial production in eight ISIC two–digit manufacturing industries in a set of 10 European nations. Results for industrial production in the G7 countries are presented in Appendix 1; any significant differences from the European results are noted in the discussion. Because results based on one–digit employment within the U.S. are not strictly comparable to results based on two–digit manufacturing production across countries, the disaggregate VAR/factor model is also estimated using annual data that are more comparable: growth in employment in six one–digit industries in the U.S.'s eight BEA regions and in a set of eight European nations.[9] Appendix 2 lists the regions and industries included and provides detail on the data.

3.3 Quarterly benchmark results

Table 1 presents benchmark results for quarterly, within–U.S. employment growth. For the average *region–industry* unit within the U.S., idiosyncratic shocks are the most important source of innovation variance, accounting for 49.1 percent. Industry–specific shocks are the second most important source of variation, with a variance share of 25.3 percent. Common and region–specific

[9] The chain–weighted real GSP data now made available by the BEA span only 1977-94, too short a period for reliable model estimation. This paper limits, admittedly somewhat arbitrarily, model estimation to datasets with at least 20 years of raw data.

shocks are of basically equal importance, with innovation variance shares of 13.0 and 12.6 percent, respectively. For the average *aggregate region*, common and region–specific shocks are the leading sources of variation, each accounting for 32.2 percent of the innovation variance. Idiosyncratic shocks are next in importance, with an innovation variance share of 23.1 percent.[10] The remaining 12.5 percent of the average region's innovation variance is due to industry–specific shocks.

Over time, there appears to be little propagation of shocks across regions and industries in the within–U.S. disaggregate model estimates. At both the region–industry and aggregate region levels, the reported steady–state variance shares are qualitatively the same as the innovation variance shares. Moreover, further decomposing the sources of variation for each region–industry and each aggregate region to obtain shares due to own vs. other region shocks and own vs. other idiosyncratic shocks reveals that the "other" components are essentially the same in the steady–state as at impact (the "other" components are 0 at impact, by construction). In this sense, then, over time there is little net propagation of shocks across regions and industries in the disaggregate model estimates. As discussed in section 5.1, this finding, in conjunction with stronger evidence of propagation from a more aggregate and less restrictive specification, suggests the disaggregate VAR model may overly restrict feedback.

Table 2 reports benchmark estimates for quarterly growth in industrial production across Europe. For the average *region–industry* unit in Europe, idiosyncratic shocks are the leading source of variation, with an innovation variance share of 59.0 percent. Region–specific shocks are the second most important source of variation, with a variance share of 22.6 percent. Common and industry–specific shocks are roughly equal in importance, with innovation variance shares of 7.7 and 10.7 percent, respectively. For the average *aggregate region*, region–specific shocks are the most important source of innovation variance, accounting for 46.4 percent. The second largest source of

[10] In this respect and all others discussed below, however, what is true on average is not necessarily true for each region or nation.

variation for the average region is idiosyncratic shocks, with an innovation variance share of 35.0 percent. Common shocks account for 13.1 percent of the innovation variance. Finally, the share of innovation variance attributable to industry–specific shocks is 5.6 percent. Appendix 1's Table A1.1 shows that results are qualitatively the same for the G7 nations.

Over time, there appears to be little propagation of shocks across nations and industries in the disaggregate model estimates for Europe and the G7. The steady–state decompositions are essentially the same as the innovation variance decompositions. But as shown in section 5.1, a more aggregate and less restrictive VAR model implies much richer propagation of shocks, suggesting the disaggregate VAR model may overly restrict feedback.

While Table 2's benchmark estimates assume the sources of variation in Europe have been stable over the 1975-97 period, the integration of nations has probably increased, due to forces such as the launching of the EMS in 1979. Unfortunately, however, data limitations and the large scale of the model rule out testing for shifts in the disaggregate VAR/factor model estimates. Therefore, to test for shifts in the sources of variation, industries are dropped from the model, and total industrial production, which is available for a longer sample period, is used in lieu of manufacturing production. Since industry–specific shocks are minor sources of variation in the disaggregate model estimates for Europe, dropping industries should not much affect the conclusions on stability. Moreover, section 4.2 presents formal evidence that dropping industries generally does not affect broad conclusions on the sources of variation.

More specifically, to test for shifts in the sources of variation a VAR(4) and the simple error model

$$e_{r,t} = \delta_r c_t + u_{r,t} \tag{9}$$

are fit to quarterly growth in industrial production for the 10 European nations listed in Table 2.[11] The sample period is divided almost exactly in half, into subsamples of 1962:2-79:4 and

[11] The error model is estimated using the GMM procedure, described in section 5.1, applied to the aggregate

1980:1-97:4, between which the parameters of the error model are allowed to differ. According to these estimates, there has been no significant shift in the average shares of variance attributable to common and nation–specific shocks.[12] On average, common shocks account for 21.8 (17.4) percent of the innovation (steady–state) variance over 1962-79 and 16.4 (14.8) percent of the innovation (steady–state) variance over 1980-97; the change in the innovation variance shares has a standard error of 5.4. To the extent this finding of stability may be viewed as suggesting integration has increased only gradually and modestly, the disaggregate model results based on 1975-97 data should accurately reflect the relative importance of different types of shocks over the period.

Comparing the quarterly within–U.S. and cross–country results reveals three general differences. First, common shocks account for a smaller share of variance in international data than in within–U.S. data. Second, region–specific innovations are more important internationally than within the U.S. Finally, industry–specific innovations account for less variation internationally than within the U.S. Note that, using the Monte Carlo standard errors reported in Table 1 as a rough guide to sampling uncertainty, these differences between the within–U.S. and cross–country estimates would appear to be statistically significant. For the remaining source of variation, idiosyncratic shocks, the relative importance varies with the set of international countries used: compared to the U.S., idiosyncratic shocks are more important in the European nations but of roughly equal importance in G7 countries.

While comparing the within–U.S. and cross–country estimates might also be seen as suggesting that the shocks affecting nations are much larger than those affecting regions within the U.S., differences in the underlying data preclude making such a comparison. The variance of the overall reduced–form shock to each region, estimated from the model parameters and reported in the second

VAR/factor model.

[12] While no change occurs on average, some individual countries' variance shares do shift significantly, with some rising and others falling. Modifying the specification by using different lag lengths or allowing the regression parameters of the VAR to shift sometimes produces a significant decline in the average share of variance attributable to common shocks.

column of each table, is much larger for European nations than for U.S. regions. This overall shock reflects the common, region–specific, industry–specific, and idiosyncratic components included in the VAR/factor model. Comparing these estimates is problematic because the within–U.S. results are for total employment in a region, while the international results are for industrial production in manufacturing in a nation. The greater volatility in the international data may simply reflect the facts that: (1) the manufacturing industry is more volatile than an overall economy; and (2) industrial production is more volatile than employment (at least in the U.S.).

3.4 Benchmark results for annual data comparable within the U.S. and across countries

Table 3 presents benchmark results for annual, within–U.S. employment growth. As detailed in Appendix 2, these estimates are based on a slightly restricted set of industries, so as to match as best as possible the available international data. For the average *region–industry* unit within the U.S., common shocks are the leading source of variation at the annual frequency, accounting for 42.6 percent. Industry–specific shocks have the second–largest innovation variance share, at 26.6 percent. Region–specific and idiosyncratic shocks are of essentially equal importance, with innovation variance shares of 15.2 and 15.5 percent, respectively. At the *aggregate region* level, common shocks are an even more important source of fluctuations, with an innovation variance share of 71.5 percent. Region–specific shocks are second in importance, accounting for 20.4 percent of the variance. Industry–specific and idiosyncratic shocks are relatively unimportant, with variance shares of 4.6 and 3.4 percent, respectively. A decomposition of steady–state variance is not reported because of computational difficulties. In this and some other annual datasets, the restricted VAR implied by the disaggregate model regression estimates has explosive autoregressive roots. Based on the quarterly results discussed above, however, if it could be calculated the steady–state decomposition would probably closely resemble the innovation variance decomposition.[13]

[13] The problem stems in part from the sometimes strong collinearity, in annual data, among the regressands in (2). Dropping the lags of the common variable X_t from the regression produced little change in the innovation variance decompositions and, in most cases, eliminated the problem of explosive roots. In these alternative

Table 4 presents estimates for annual employment growth in a comparable set of industries within European countries. For the average *region–industry* unit in Europe, idiosyncratic shocks have the largest innovation variance share, at 40.0 percent. Region–specific shocks are second in importance, accounting for 28.2 percent of the variance. Common and industry–specific shocks are of nearly equal importance, with shares of 13.6 and 18.2 percent, respectively. At the *aggregate region* level, the largest share of variation, 36.6 percent, is due to region–specific shocks. Common, industry–specific, and idiosyncratic shocks are of roughly equal importance, with variance shares of about 20 percent. However, in the G7 estimates shown in Appendix 1's Table A1.2, industry–specific shocks are somewhat less important than either common or idiosyncratic shocks.

These benchmark results for comparable annual data, in conjunction with the results for quarterly data, suggest three broad conclusions. First, common shocks are less important in international fluctuations than in within–country fluctuations. Second, region–specific shocks are a larger source of variation in international data than in within–U.S. data. Third, at the quarterly frequency, which as discussed below probably yields more accurate variance decompositions, industry–specific shocks are less important in international variation than in within–U.S. variation. But at the annual frequency, the reverse applies.[14] By themselves, the benchmark estimates for comparable annual data also suggest that the shocks affecting nations are modestly smaller than those affecting regions within the U.S. The fitted variance of the overall reduced–form shock to each region averages 2.478 for U.S. regions and 1.380 for European nations.[15]

3.5 Comparison with previous results using same basic approach

Several studies have relied on specifications very similar to the disaggregate VAR/factor model

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results, the steady–state variance decompositions are qualitatively very similar to the reported innovation variance decompositions.

[14] However, the importance of industry–specific shocks in annual data is more comparable between the U.S. and the G7 than between the U.S. and Europe. As can be seen from Appendix 3's Table A1.2, if Italy is excluded the average importance of industry–specific shocks in the G7 is about the same as within the U.S.

[15] Although Wynne and Koo (1997) also find that employment is more volatile within the U.S. than across European nations, their estimates indicate GDP is equally volatile within the U.S. and across Europe.

underlying the benchmark results: Altonji and Ham (1990), Helg, et. al. (1995), Krieger (1989), and Norrbin and Schlagenhauf (1988, 1996). On net, the general conclusions drawn from the benchmark estimates are very much in line with the results of these previous studies.

Altonji and Ham use the model, with some additional restrictions on the coefficients of (2) and (3), to investigate the sources of variation in annual, 1961-82 data on employment in one–digit industries in Canadian provinces.[16] Their model is also augmented to include current and lagged U.S. GNP growth in (2), to capture the potentially considerable influence of the neighboring U.S. In qualitative terms their estimates are broadly similar to those reported above for annual U.S. data. Abstracting from the important effect of the U.S. on Canada, common shocks are the leading source of variation in the *average region*, accounting for 33 percent of the innovation variance. Region–specific shocks are also important, although less so than common shocks, with an innovation variance share of 17 percent. Industry–specific shocks play only a small role in variation in Canadian regions. Altonji and Ham's results are only qualitatively different from the above results for annual U.S. employment in that idiosyncratic shocks are a significant source of variation, roughly equal in importance to region–specific shocks.

Helg, et. al. (1995) examine the sources of fluctuations in European industrial production using a disaggregate VAR and principal components analysis of the residuals. They estimate a variant of (2) with quarterly, 1975–92 data for 11 two–digit and three–digit industries in 11 European nations. The Helg, et. al. equation differs from (2) in that: aggregate growth X_t is dropped from the set of regressands; the region and industry aggregates $X_{r,t}$ and $X_{i,t}$ included in the equation for $X_{r,i,t}$ are defined to exclude $X_{r,i,t}$; and lags of $X_{r,i,t}$ are added to the set of regressors. Rather than fit a formal error model to the residuals, Helg, et. al. use principal components analysis to gauge the relative importance of region–specific and industry–specific shocks. They compute principal

[16] Text discussions of sample periods generally refer to the sample of raw data, rather than the sample used in estimation after allowing for differencing and model lags. In some cases, however, the sample reported by authors may reflect the estimation period rather than the sample of raw data.

components for the set of industries within each country (country PCs) and for the set of countries given a particular industry (industry PCs). The estimates show that, on average, the country PCs explain more of the variation in nation–industry production than the industry PCs do, suggesting nation–specific shocks are more important than industry–specific shocks.

Krieger (1989) relies on a variant of the disaggregate VAR/factor model to examine the sources of variation in annual, 1961-84 GNP data for one–digit industries in Canada, West Germany, and Japan. Like Altonji and Ham (1990), Krieger augments (2) to include current and lagged U.S. GNP growth. Krieger's specification also differs from the benchmark model in that (2) is augmented to include a lag of region–industry growth and the common shock is excluded.[17] Krieger's basic results are consistent with this paper's benchmark results for annual international data. Specifically, at the level of the average *region–industry*, Krieger's estimates show that, abstracting from the important role of U.S. disturbances, idiosyncratic shocks are the most important source of variation, followed by country–specific and in turn by industry–specific shocks. At the level of the *average nation*, country–specific shocks are the most important source of variance, apart from U.S. shocks, with an innovation variance share of 27 percent. Industry–specific and idiosyncratic shocks are of lesser and essentially equal importance, accounting for 13 and 11 percent, respectively, of the innovation variance.[18]

Norrbin and Schlagenhauf (1988) apply a specification like the disaggregate VAR/factor model to quarterly, 1954-84 data on employment in one–digit industries in U.S. regions, defined as the Census Bureau's nine aggregate regions. While Norrbin and Schlagenhauf's specification is broadly similar to the benchmark model used above, there are several specific differences. First, Norrbin and Schlagenhauf specify the model in DYMIMIC form (described by Engle and Watson (1981)),

[17] In some supplementary results that are reported to be similar to the baseline results, Krieger allows the region–specific shocks to be correlated.

[18] Krieger finds that the decomposition of steady–state variance is slightly different, with country–specific and idiosyncratic shocks of equal importance and industry–specific shocks of less importance.

relating the unobserved components to causal variables such as monetary and fiscal policy indicators. Second, Norrbin and Schlagenhauf restrict the number of lags included in (2) to two but allow the common, region–specific, and industry–specific components to follow AR(1) processes. Finally, the regression equation (2) is augmented to include the weighted average of current growth in international industrial production.

Norrbin and Schlagenhauf's (1988) specification yields estimates that are similar to the benchmark results in some, but not all, respects. The estimates are comparable in that, in terms of the sources of steady–state variation for the average *aggregate region*, common shocks are a leading source. In the Norrbin and Schlagenhauf results, common shocks account for 47 percent of the average region's variance. In the benchmark estimates, common shocks are also a leading source of variation, although they are no more important than region–specific shocks. Compared to the benchmark, Norrbin and Schlagenhauf's estimates differ in that region–specific shocks are much less important and industry–specific shocks are more important, with respective variance shares of 11 and 28 percent. These discrepancies in results appear to be largely a function of differences in lag length and sample period. Reestimating the benchmark model with just two lags in (2) and 1956-84 data, specifications comparable to Norrbin and Schlagenhauf's, produces results quite similar to theirs.[19] At any rate, Norrbin and Schlagenhauf's estimates are consistent with the general conclusions reached above: when international results are compared to within–U.S. results, common shocks are less important, region–specific shocks are more important, and industry–specific shocks are less important (in quarterly data).

Norrbin and Schlagenhauf (1996) use a model similar to (2)–(3) to examine the sources of cross–country fluctuations in quarterly, 1956-92 industrial production in two–digit industries. The countries include the G7 plus Belgium and the Netherlands. The industries cover mining (one

[19] Specifically, the steady–state variance shares for the average region are: common, 44.5 percent; region–specific, 17.7 percent; industry–specific, 21.6 percent; and idiosyncratic, 16.1 percent.

industry), manufacturing (eight), and utilities (one). While very comparable, Norrbin and Schlagenhauf's specification differs from the disaggregate VAR/factor model in several respects. First, their version of (2) replaces the world growth variable X_t in (2) with an export share–weighted average of other countries' aggregate growth rates, a variable which corresponds to world growth from the export perspective of each particular region–industry. Second, Norrbin and Schlagenhauf's specification of (2) replaces the lags of industry growth variable $X_{i,t}$ with lags of the dependent variable, $X_{r,i,t}$. Third, Norrbin and Schlagenhauf allow the common, region–specific, and industry–specific components to follow AR(1) processes.

Norrbin and Schlagenhauf's (1996) estimates are broadly similar to the benchmark results for international industrial production discussed above. In Norrbin and Schlagenhauf's results, as in the benchmark, region–specific and idiosyncratic shocks are the leading sources of variation for the *average country.* The exact order of importance, however, differs. While the benchmark results indicate region–specific shocks are more important, Norrbin and Schlagenhauf's estimates indicate idiosyncratic shocks are more important than region–specific shocks, with shares of 40 and 34 percent, respectively. The importance of world and industry–specific shocks is roughly the same in the benchmark and Norrbin and Schlagenhauf estimates. Norrbin and Schlagenhauf report world and industry–specific shock shares of 16 and 10 percent.

4. Alternative Data Specifications and Data Issues

The benchmark results presented in the previous section rely on particular datasets — for example, quarterly employment growth for one–digit industries across the BEA regions of the U.S. The use of these datasets entails making choices with respect to the levels of time–series and cross–section aggregation, business cycle indicator, and trend model.[20] This section reviews the issues to be considered in making these choices and the available evidence from existing research on how

[20] The results seem to be relatively insensitive to another element of the data specification, the modeling of seasonals. The only general sensitivity evident is that data adjusted using seasonal dummies tend to yield modestly larger variance shares for common shocks and smaller variance shares for region–specific shocks than X–11 filtered data do.

some of those choices affect results. This section also augments the existing evidence by presenting some results on how choices different from those of the benchmark affect conclusions.

4.1 Time–series aggregation

One important element of any data specification is the level of time–series aggregation: the choice of monthly, quarterly, or annual data. Some studies in the literature, such as Coulson (1993), Coulson and Rushen (1995), and Lumsdaine and Prasad (1997), rely on monthly data. Most research, however, relies on either quarterly or annual data. Studies based on quarterly data include Clark (1988), Helg, et. al. (1995), Norrbin and Schlagenhauf (1988, 1996), and Stockman (1988), among others (Tables 9 and 10, discussed below, provide a more complete listing for studies reporting decompositions of variance into components that are common, region–specific, etc.). Studies using annual data include Altonji and Ham (1990), Bayoumi and Prasad (1997), Coulson (1993), and Krieger (1989), among others.

Using monthly or quarterly data offers two advantages. As discussed by Altonji and Ham (1990), among others, the importance of region–specific and industry–specific shocks should be measured more accurately in monthly or quarterly data than in annual data. If over time the shocks propagate across regions and industries, annual data may understate the importance of region–specific and industry–specific shocks and overstate the importance of common shocks. Moreover, monthly or quarterly data offer the computational advantage that more degrees of freedom are available, while annual data offer fewer degrees of freedom, making some computations more difficult or infeasible.

However, using monthly or quarterly data also has some disadvantages. The higher frequency data are probably more subject to measurement error than annual data are. In the U.S., for example, movements in monthly employment are based on sampling methodology, while annual data are benchmarked to nearly complete censuses of employment (Social Security records). Such measurement error could significantly contaminate estimates of the sources of fluctuations. Moreover, monthly and quarterly data are less widely available than annual data. As examples, the only available measure of production in U.S. regions is annual value added, and industry employment by country is only widely available on an annual basis. In light of such availability problems, only annual data allow close comparisons of within–U.S. and cross–country results.

The limited existing evidence suggests that results are only modestly sensitive to the choice of data frequency. Norrbin and Schlagenhauf (1988) report that using annual, within–U.S. data does not alter the relative importance of the shocks evident in their quarterly estimates. Norrbin and Schlagenhauf (1996) conclude that using semiannual rather than quarterly data on international production has effects that vary by country, but their steady–state variance estimates show that, for the average *country*, using semiannual data modestly raises the importance of world shocks, modestly lowers the importance of country–specific shocks, slightly raises the importance of industry–specific shocks, and slightly lowers the importance of idiosyncratic shocks. Norrbin and Schlagenhauf (1996) note that using annual data significantly increases the importance of industry–specific shocks.

Some systematic sensitivities emerge, however, when the quarterly benchmark estimates are compared to estimates from annual averages of the same data. In particular, using annual rather than quarterly data consistently boosts the importance of common shocks and lowers the importance of idiosyncratic shocks.[21] Tables 5 and 6 report estimates for annual data on, respectively, within–U.S. employment and cross–Europe industrial production (Appendix 1's Table A1.3 presents G7 results).[22] For the average U.S. *region*, the shares of innovation variance attributable to common and idiosyncratic shocks are 66.8 and 4.7 percent, respectively, in annual data (Table 5), compared

[21] In the case of the *aggregate* VAR/factor model discussed in section 5.1, using annual, rather than quarterly, within–U.S. data boosts the importance of common shocks and lowers the importance of region–specific and industry–specific shocks.

[22] As noted above, the annual data estimates are based on a lag length of one in (2). The annual, within–U.S. employment estimates in Table 5 differ from those in Table 3 in two respects. First, the data span 1956-97 rather than 1970-93. Second, all eight one–digit industries are used, rather than the six used in the Table 3 estimates. Despite these differences, the estimates reported in Tables 3 and 5 are very similar.

to 32.2 and 23.1 percent in quarterly data (Table 1). For the average European *nation*, the innovation variance shares of common and idiosyncratic shocks are 37.6 and 16.8 percent, respectively, in annual data (Table 6), compared to 13.1 and 35.0 percent in quarterly data (Table 2). The sensitivity of the importance of region–specific and industry–specific shocks varies by dataset and level of aggregation. For instance, in within–U.S. data, using annual rather than quarterly data does not affect the importance of region–specific shocks to the average *region–industry* but lowers the importance of region–specific shocks to the average *region*.

While this analysis shows that the choice of data frequency does affect estimates, the broad conclusions drawn above apply to either quarterly or annual data. As long as the frequency of the data is the same in the within–U.S. and cross–country estimates being compared, common shocks are less important internationally than within the U.S. and region–specific shocks are more important internationally. Moreover, in quarterly data, industry–specific shocks are less important in international variation than in within–U.S. variation, but in comparable annual data, the reverse applies.

4.2 Cross–section aggregation

A second key aspect of any data specification is the degree of cross–section aggregation: the choice of within–country region detail, such as states or BEA regions for the U.S., and the choice of industry detail, such as one–digit, two–digit, or none. The vast majority of within–country studies, including Bayoumi and Prasad (1997), Clark (1998), Norrbin and Schlagenhauf (1988), and others, use aggregate regions. However, some researchers, including Davis, et. al. (1997), Ghosh and Wolf (1997), Hooker and Knetter (1997), and Viñals and Jimeno (1996) rely on U.S. state data rather than aggregate region data. At an even more disaggregate level, Forni and Reichlin (1997) use U.S. county data, and Marston (1985) examines U.S. city data.[23] While these disaggregate region

[23] A few studies have focused on a particular region in the U.S., rather than a full set of regions spanning the country. Coulson (1993), Coulson and Rushen (1995), and Kuttner and Sbordone (1997) examine, respectively, the Philadelphia, Boston, and New York metropolitan areas.

studies and others such as Bayoumi and Eichengreen (1993) and Lumsdaine and Prasad (1997) ignore industries and focus on just region variables, most of the literature examines fluctuations in one–digit industries. However, a number of studies, such as Costello (1993), Ghosh and Wolf (1997), Helg, et. al. (1995), and Norrbin and Schlagenhauf (1996), analyze two–digit industries.[24]

Relatively aggregate data offer the important advantage of greater tractability. With R regions and I industries, the disaggregate VAR/factor model, for example, involves RI variables. Using relatively aggregate data generally keeps R and I smaller than using disaggregate data would and thereby makes estimation of the model's system of equations computationally much simpler and faster.[25] Relatively aggregate within–country *region* data offer another advantage: aggregates such as BEA regions are more comparable in size to G7 or European nations than states are and therefore more appropriate for within–country and international comparisons. Relatively aggregate *industry* data offer two other advantages. First, given the differences in U.S. and international industry classification systems, it is easier to construct highly comparable within–U.S. and cross–country datasets at the one–digit level than at more detailed levels. Second, one–digit data are, to some extent, more widely available. For example, missing data are much more of a problem for employment in two–digit industries within U.S. regions than for employment in one–digit industries. In some circumstances, however, two–digit industry data are more widely available. Particularly, at the quarterly frequency, the only widely available measure of production across countries is industrial production in two–digit industries.

Using relatively aggregate region data carries one disadvantage. In the U.S., many of the potential region–specific shocks occur directly at the state and local, rather than aggregate region, levels. For example, fiscal policies (apart from federal policies) are determined at the state and local

[24] Ghosh and Wolf (1997) use a combination of one–digit and two–digit industries that spans the entire U.S. economy.

[25] Typically, the available two–digit data are limited to the manufacturing sector. Under the United States' SIC classification code, there are only eight one–digit nonfarm sectors, but 20 two–digit sectors in manufacturing alone. Under the international classification code (ISIC), however, the number of one–digit nonfarm sectors is essentially the same as the number of two–digit manufacturing sectors.

levels; there are no BEA region (or Census Region) fiscal policies. The BEA regions are simply aggregations of states with commonalities in certain features, not governments.

While the broad conclusions on sources of fluctuations are insensitive to the degree of cross–section aggregation, specific model estimates do appear to be modestly sensitive. Estimating the benchmark quarterly model for U.S. state employment yields innovation variance shares for the average *state* of: common, 21.5 percent; region–specific, 29.5 percent; industry–specific, 6.3 percent; and idiosyncratic, 43.2 percent.[26] As these estimates indicate, using states rather than BEA regions (for which Table 1 reports results) modestly lowers the importance of common and industry–specific shocks and significantly boosts the importance of idiosyncratic shocks, while leaving the variance share of region–specific shocks essentially unchanged. Nonetheless, when U.S. state estimates are compared to the quarterly cross–country estimates, it remains the case that common shocks are less important internationally than within the U.S. while region–specific shocks are more important internationally.[27] However, industry–specific shocks are of roughly equal importance in the U.S. state and international results, rather than of greater importance as in the BEA region results.

Models that ignore industries also produce estimates somewhat different from the benchmark but in line with the broad findings discussed above. Fitting a VAR(4) and the simple error model (9) to quarterly growth in total employment in BEA regions yields average common and region–specific shock shares of 49.7 and 50.3 percent for the innovation variance and 32.2 and 67.8 percent for the steady–state variance.[28] Applying a VAR(4) and (9) to quarterly growth in European manufacturing production, the average estimated common shock shares are 29.6 and 18.4 percent

[26] The model covers only 41 states, because any states having data missing over 1956-97 for any industry were dropped for simplicity. The model also excludes the mining industry, so as to speed the estimation. Including the mining industry, which is especially volatile, generally requires many more iterations of the algorithm. Results for BEA regions are not sensitive to whether mining is included. Estimating the state–industry model with quarterly data took about four days on a Unix machine, using somewhat inefficient code in RATS.

[27] Similarly, in dynamic factor model estimates for total employment in states and BEA regions and for total manufacturing production in European nations and the G7, the common factor is less important internationally than for BEA regions or for states, while region–specific factors are more important internationally.

[28] The error model is estimated using raw 1947-97 data and the GMM procedure, described in section 5.1, applied to the aggregate VAR/factor model.

for, respectively, innovation and steady–state variances, and the estimated region–specific shock shares are 70.4 and 81.5 percent. Compared to the benchmark estimates, ignoring industries typically boosts the importance of both common and region–specific shocks.[29] The specific effects of ignoring industries depend on the true magnitudes of industry–specific shocks and the heterogeneity in industry mix. For example, abstracting from the underlying sizes of the shocks, if the widely–held view that industry mix varies more across U.S. regions than across countries is correct, ignoring industries would probably boost the importance of common shocks relatively more in cross–country data than in within–U.S. data.[30] Nonetheless, in estimates that ignore industries, it remains the case that common shocks are less important internationally than within the U.S., while region–specific shocks are more important internationally than within the U.S.

Using two–digit rather than one–digit industries also produces estimates modestly different from the benchmark but consistent with this study's broad findings. While within–U.S. data availability problems preclude estimating the disaggregate VAR/factor model for two–digit industries, estimating the *aggregate* VAR/factor model discussed in section 5.1 for two–digit manufacturing industries yields innovation variance shares that are, on average, essentially the same as for one–digit industries.[31] The steady–state variance shares, however, are somewhat different, with region–specific shocks of less importance and industry–specific shocks of more importance in the two–digit results. Comparing disaggregate model estimates for annual cross–country data on employment and GDP (Appendix 2 provides detail on the data) shows that using two–digit manufacturing industries

[29] Comparing the region–only results to the aggregate VAR/factor model results discussed in section 5.1 shows that ignoring industries usually boosts the estimated importance of common shocks but has little effect on the importance of region–specific shocks.

[30] Whether industry mix is more varied across U.S. regions or countries appears to depend on the level of industry aggregation. Bayoumi and Prasad (1997) conclude that, at the one–digit level, the mixes of U.S. regions and European nations are equal in heterogeneity. Krugman (1991), however, concludes that there is significantly more specialization of two–digit manufacturing industries in the U.S. manufacturing than in Europe.

[31] The VAR variables are the growth rates of total manufacturing employment in the eight BEA regions and in 19 U.S. two–digit manufacturing industries (tobacco is excluded because the industry is concentrated in one region). Averaged across regions, the estimated innovation variance shares of common, region–specific, and industry–specific shocks are 28.4, 52.5, and 19.1 percent, respectively. The estimated steady–state variance shares are 10.3, 29.2, and 60.5 percent, respectively.

typically boosts the importance of common shocks and lowers the importance of industry–specific and idiosyncratic shocks, while having mixed effects on the importance of region–specific shocks. Qualitatively, the two–digit estimates yield the same conclusions as those drawn above from the one–digit estimates.[32]

4.3 Business cycle indicator

A third important aspect of data specification is the business cycle measure used: output as measured by GDP or industrial production, employment, unemployment, or productivity. Results for GDP are reported in Bayoumi and Eichengreen (1993), Bayoumi and Prasad (1997), Gregory, et. al. (1997), and Krieger (1989), as well as others (Tables 9 and 10 provide a complete list of those papers reporting variance decompositions).[33] Studies examining industrial production include Helg, et. al. (1995), Norrbin and Schlagenhauf (1996), and Stockman (1988). Papers relying on employment include Altonji and Ham (1990), Clark (1998), and Norrbin and Schlagenhauf (1988), among others. Unemployment is examined in Davis, et. al. (1997), Marston (1985), and Viñals and Jimeno (1996). Costello (1993), Hess and Shin (1997, 1998), and Kollman (1995) examine productivity.

In practice, the key consideration in choosing a business cycle measure is data availability. In general, many economists probably view GDP as a preferred variable for examining business cycle fluctuations, although, for particular questions, other indicators may be preferred.[34] GDP data, however, are less widely available than industrial production or employment data. For example, cross–country data on GDP by industry are generally only available on an annual basis, whereas

[32] However, a fact highlighted by Costello (1993) and Kollman (1995) appears to apply only to two–digit data. At the two–digit level, consistent with Costello and Kollman, annual employment growth (and GDP growth) is more correlated across industries within a country than across countries within an industry. But at the one–digit level, the within–country and within–industry correlations are, on average, roughly the same. Consistent with Kollman, for U.S. regions, growth is less correlated across industries within a region than across regions within an industry — at both the one–digit and two–digit levels.

[33] Forni and Reichlin (1997) and Samolyk (1994) examine within–U.S. personal income.

[34] The findings of Basu and Fernald (1995) may be seen as suggesting GDP should not be preferred for examining within–country and cross–country fluctuations. Basu and Fernald argue that value added data can imply large spillovers across sectors even when such spillovers do not truly exist, because the value added data are based on the false assumptions of constant returns to scale and perfect competition.

industrial production data are available quarterly. As another example, real GDP data by U.S. region (gross state product, or GSP) are only available on an annual basis beginning in 1977, while employment data are available monthly and for a longer time period.[35] As noted above, on a quarterly basis, the only broad economic indicators available by industry for substantial time periods are employment within the U.S. and industrial production across countries.[36]

A second consideration, alluded to in section 3, is the comparability of within–country and cross–country data. Industrial production, for instance, is available for different countries but not for regions within the U.S. While Chamie, et. al. (1994) use U.S. regional industrial production figures, the data are not truly regional. Their U.S. data, constructed by DRI, are aggregates of *national* industrial production indexes by detailed industry based on region–specific weights. The only available data closely comparable within the U.S. and across countries are annual employment and annual GDP (GSP for U.S. regions), although the within–U.S. GDP data are available for less than 20 years.

The limited analysis possible shows that estimates are modestly sensitive to the choice of business cycle indicator, although not systematically. In international data (detailed in Appendix 2), estimates for GDP differ somewhat from estimates for employment. For example, estimating the disaggregate VAR/factor model for cross–Europe GDP (using the same countries and industries included in the employment estimates) yields the following innovation variance shares for the average *nation*: common, 23.2 percent; region–specific, 49.2 percent; industry–specific, 14.2 percent; and idiosyncratic, 13.5 percent. Comparing these and other cross–country estimates indicates that there are no systematic differences in GDP and employment estimates. Ultimately, using GDP produces the same general conclusions that using employment does.

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[35] As noted above, the real GSP data available from the Regional Economic Information Systems CD–ROM begin in 1977. Some authors, such as Ghosh and Wolf (1997) and Wynne and Koo (1997), construct real GSP data back to 1963 using the available nominal figures by region and national price indexes.

[36] In addition, earnings by industry are available on a quarterly basis for regions within the U.S. beginning in 1969.

4.4 Modeling trends and unit roots

The final important aspect of data specification is the modeling of trends and unit roots. Many data series of interest have a trend and most have a largest autoregressive root of 1 or nearly 1. Clark (1998), Helg, et. al. (1995), and Norrbin and Schlagenhauf (1996), among others, report that the null of a unit root generally cannot be rejected. These results establish that most series of interest have autoregressive roots of near 1, but the results are not necessarily strong evidence of roots equal to 1, given the power problems of unit root tests (see Campbell and Perron (1991), for example). The limited evidence on cointegration is more mixed — and probably more uncertain given that, in small samples, multivariate inference is likely more imprecise than univariate inference. In regional U.S. employment data, Sill (1997) finds evidence of cointegrating relationships. In international data, Engle and Kozicki (1993) are generally unable to reject the null of no cointegration, but Helg, et. al. (1995) find cointegration among many of their series.

Studies of the sources of business cycles typically treat any trends as stochastic and use any of several different approaches to modeling unit roots or near–unit roots. Most research in the literature assumes all variables have a unit root but are not cointegrated, and works with simple log growth rates. Of course, if the absence of cointegration is simply assumed and the variables are in fact cointegrated, the model in differences in misspecified. Some studies, such as Helg, et. al. (1995), assume unit roots in all variables and allow cointegration of an unrestricted form by adding lagged levels to the model. This approach is equivalent to estimating the model in log levels, which yields consistent VAR parameter estimates regardless of the integration orders of the data. However, estimates may be biased in small samples, and if the variables are cointegrated, steady–state variance decompositions may be inconsistent (see Phillips (1998)). Other studies, such as Sill (1997), explicitly model cointegrating relationships. The disadvantage of this approach is that correctly determining cointegrating relationships among a large number of variables in a small sample of data is difficult (see Gonzalo and Pitarakis (1994) and Ho and Sorenson (1996)).

Some studies in the literature, however, use two–sided moving average filters to remove trend components from data series. Gregory, et. al. (1997) and Hess and Shin (1997, 1998), for example, use data detrended with the filter of Hodrick and Prescott (1997) (hereafter, the H–P filter). Wynne and Koo (1997) detrend data with the band–pass filter developed by Baxter and King (1995). While the moving average filter approach may be seen as having the advantage of simply isolating fluctuations at business cycle frequencies, it suffers the disadvantage of potentially exaggerating cyclical fluctuations, producing cyclical components from data truly having no cyclical component (see Cogley and Nason (1995), for example).

The VAR/factor model estimates reported in this paper appear to be largely insensitive to alternative treatments of trends, with one qualification.[37] The qualification is that disaggregate models in unrestricted error correction form (log levels) and for HP–filtered data are more prone to having explosive autoregressive roots. But abstracting from this problem, estimates for log levels and HP–filtered data are very similar to the benchmark estimates based on growth rates.[38] For example, fitting the disaggregate VAR/factor model to HP–filtered, within–U.S. employment data yields innovation variance shares, averaged across aggregate regions, of 31.3, 31.5, 12.5, and 24.7 percent for, respectively, common, region–specific, industry–specific, and idiosyncratic shocks.

5. Variations on the Disaggregate VAR/Factor Model Approach

In addition to relying on particular datasets, the benchmark results presented in section 3 are based on a particular model, the disaggregate VAR/factor model. This section reviews some alternative, but closely related, approaches used in the literature. Like the disaggregate VAR/factor

[37] The similarity across trend treatments is evident in not only the disaggregate VAR/factor model estimates but also the aggregate VAR/factor model estimates. As noted below, however, Gregory, et. al. (1997) find that dynamic factor model estimates for the G7 are modestly sensitive to the use of HP–filtered data rather than growth rates.

[38] The "log levels" estimates use the regression (2) in log levels, rather than growth rates, and augmented to include lags of the dependent variable. The lagged dependent variable was included to make the levels model analogous to an unrestricted error correction form. Adding the lagged dependent variable also facilitated obtaining convergent parameter estimates in both the "log levels" and H–P filtered models. Accordingly, the reported results for H–P filtered data also use a version of (2) augmented to include lags of the dependent variable.

model, these alternative formulations include an error model that decomposes innovations into unobserved components that are common, region–specific, etc. More specifically, this section reviews: *aggregate* VAR/factor models; models that combine a VAR with alternative schemes for identifying common and region–specific shocks; and dynamic factor models. In several instances, results from existing studies are augmented with new results directly comparable to the benchmark estimates.

5.1 The aggregate VAR/factor model

Two recent studies, Clark (1998) and Kuttner and Sbordone (1997), use an aggregate version of the benchmark model (2)–(3). In this specification, henceforth referred to as the *aggregate VAR/factor model*, the basic variables are region aggregates and industry aggregates. In the within–U.S. specification discussed below, the variables in the model include the growth rates of total employment in BEA regions and of total U.S. employment in one–digit industries. In the cross–country specification considered below, the model variables are the growth rates of total manufacturing production in a set of European (or G7) nations and "world" production in two–digit manufacturing industries (where "world" consists of the included countries).

More specifically, letting Z_t denote the $(R+I)\times 1$ vector of aggregate region and industry growth rates and $e_{r,t}$ and $e_{i,t}$ represent the error terms for the region r and industry i equations, the model takes the form

$$Z_t = \sum_{p=1}^{P} \Psi_p Z_{t-p} + e_t \tag{10}$$

$$e_{r,t} = \delta_r c_t + u_{r,t} + \sum_i a_{r,i} n_{i,t} \tag{11}$$

$$e_{i,t} = \delta_i c_t + \sum_r b_{r,i} u_{r,t} + n_{i,t}. \tag{12}$$

c_t, $u_{r,t}$, and $n_{i,t}$ represent unobserved common, region–specific, and industry–specific innovations, respectively. The δ_r, δ_i, $a_{r,i}$, and $b_{r,i}$ terms of (11) and (12) measure the responses of regions and industries to the structural shocks. The δ_r and δ_i coefficients are treated as parameters to be estimated, while the $a_{r,i}$ and $b_{r,i}$ coefficients are treated as known and set equal to employment or output shares. Clark (1998) presents results for fixed $a_{r,i}$ and $b_{r,i}$ coefficients equal to average employment shares and for time–varying coefficients equal to lagged employment shares; Kuttner and Sbordone (1997) rely on similarly time–varying weights. For identification, the variance of the common shock c_t is fixed at 1.[39]

As discussed by Clark (1998), the aggregate VAR/factor model can be derived from a version of the disaggregate VAR/factor model in which the VAR coefficients in (7) are unrestricted rather than forced to take the form (8). In fact, the aggregate VAR can be shown to impose fewer coefficient restrictions on the unrestricted disaggregate model than the actual disaggregate model does. Put somewhat differently, the aggregate VAR allows for much richer feedback among regions and industries than the disaggregate model does. However, deriving the aggregate error model (11)–(12) from the disaggregate version (3) requires assuming that the law of large numbers applies to the weighted average of the idiosyncratic shocks $v_{r,i,t}$.[40] The aggregate model supposes that any covariation among aggregate regions and industries due to idiosyncratic shocks is 0.

Applying the aggregate VAR/factor model to quarterly, 1947-90 data on employment growth in U.S. Census Regions and one–digit industries, Clark (1998) obtains results qualitatively similar to the benchmark disaggregate estimates. In Clark's estimates, as in the benchmark, common and region–specific shocks are the leading sources of variation for aggregate regions, while industry–specific shocks are somewhat less important. For the average region, common, region–specific, and industry–specific shocks account for, respectively, 40, 41, and 20 percent of the innovation variance. In contrast to the benchmark, Clark's estimates reveal significant propagation of region–specific and industry–specific shocks over time. Averaged across regions, Clark's estimated shares of steady–state variance attributable to common shocks, own region–specific shocks, other region–

[39] Kuttner and Sbordone (1997) instead equivalently restrict one of the common factor loadings to equal 1.

[40] The aggregate model also imposes the restrictions $\theta_{r,i} = \sigma_{u_r}$ and $\lambda_{r,i} = \sigma_{n_i}$, where $\theta_{r,i}$ and $\lambda_{r,i}$ are response coefficients in (3), and σ_{u_r} and σ_{n_i} denote the standard deviations of the region–specific and industry–specific shocks in (11)–(12).

specific shocks, and industry–specific shocks are 17, 16, 33, and 34 percent, respectively. Similarly, applying the aggregate model to quarterly employment growth in New York, the rest of the U.S., manufacturing, finance, and other industries, Kuttner and Sbordone (1997) find that New York–specific shocks are the leading source of fluctuations in New York, accounting for 47 percent of the 4–quarter ahead forecast error variance.[41] Aggregate shocks are second in importance, with a variance share of 34 percent. The remaining 18 percent is due to industry shocks.

Estimating the aggregate VAR/factor model with aggregate data corresponding to the disaggregate data underlying the benchmark results permits even better comparison of the disaggregate and aggregate specifications. The $a_{r,i}$ and $b_{r,i}$ shares needed to estimate the aggregate model are the same fixed weights used in the disaggregate model analysis and discussed above. The VAR lag length P is set at 4 for U.S. employment growth but just 2 for growth in international industrial production, in order to conserve degrees of freedom.[42] In the within–U.S. analysis, the series used to estimate the model are actual aggregate variables (for example, total employment in New England and U.S. employment in manufacturing) rather than fixed–weight averages of region–industry variables. But in international analysis, the series used in aggregate estimation are constructed as fixed–weight averages of the disaggregate nation–industry data, since appropriate measures of "world" production, defined as production by just the included countries, are not directly available. Appendix 3 discusses some other details of the specifications used.

The aggregate VAR/factor model is estimated with Clark's (1998) two–step procedure. In the first step, the VAR (10) is estimated by OLS. In the second step, the error model equations (11)–(12) are estimated using the VAR residuals and unweighted GMM. Unweighted, rather than optimally–weighted, GMM is applied because, as shown by Altonji and Segal (1996) and Clark

[41] Kuttner and Sbordone (1997) also report estimates for a variant of the model that allows the common, region–specific, and industry–specific components to follow autoregressive processes but restricts the VAR structure such that only own–lags appear in each equation. This model produces similar results.

[42] The international results are generally unchanged when a fourth lag is added (omitting the third), although adding a fourth lag sometimes creates explosive roots in the VAR.

(1996), optimally–weighted GMM typically produces biased parameter estimates, while unweighted GMM is practically unbiased. Although GMM and ML estimation of the aggregate specification are equally tractable, GMM is used to avoid making the distributional assumption needed for ML.[43] The tradeoff is that, if in fact the data are normally distributed, GMM estimates will be less efficient than ML. At any rate, ML estimates of the within–U.S. model are qualitatively similar to the GMM estimates discussed below.

Tables 7 and 8 present estimates of the aggregate VAR/factor model for quarterly growth in within–U.S. employment and European industrial production (Appendix 1's Table A1.4 presents aggregate estimates for the G7).[44] These estimates are broadly similar to the corresponding disaggregate model estimates reported in Tables 1 and 2. For U.S. regions, region–specific shocks are the most important source of innovation variance, accounting for an average of 52.3 percent. Common shocks and industry–specific shocks are of lesser, but still substantial, importance, with roughly equal shares of 23.2 and 24.5 percent, respectively. For European nations, nation–specific shocks are the biggest source of fluctuations, accounting for an average of 75.7 percent of the innovation variance. Common shocks are a smaller, but significant, source of variation, with an innovation variance share of 20.8 percent. Industry–specific shocks have little immediate impact on European nations.

In contrast to the disaggregate VAR estimates, the aggregate VAR/factor model estimates suggest considerable propagation of region–specific and industry–specific shocks across sectors. For U.S. regions, in the steady state the share of variance due to region–specific shocks edges up to 55.7 percent, as a decline in the importance of each region's own shock is more than offset by an

[43] As long as no restrictions are imposed on the VAR coefficients, both GMM and ML estimates can be obtained with a two–step procedure.

[44] The within–U.S. aggregate specification considered in this paper differs from Clark's (1998) in several respects. First, the sample period used here ends in 1997, rather than 1990. Second, this analysis uses BEA regions rather than Census Regions. Finally (and most importantly), this paper uses data seasonally adjusted with the X–11 filter rather than dummy variables. As noted above, using dummy–adjusted data boosts the importance of common shocks.

increase in the importance of other regions' shocks. The share of variance attributable to industry–specific shocks rises to 35.3 percent. Accordingly, the importance of common shocks declines, to a variance share of 9.0 percent. For European nations, in the steady state the share of variance due to nation–specific shocks falls modestly, as a decline in the importance of each nation's own shock is less than fully offset by an increase in the importance of other nations' shocks. The share of variance attributable to industry–specific shocks increases to 20.5 percent. The importance of common shocks declines modestly, to a steady–state variance share of 13.5 percent. Given that the aggregate VAR may be viewed as imposing fewer restrictions on the disaggregate structure (7) than the estimated disaggregate model does, these findings suggest the disaggregate VAR/factor model may overly restrict feedback among regions and industries.

The effects of dropping idiosyncratic shocks in moving from the disaggregate model to the aggregate model can be roughly gauged with some simple calculations. The aggregate error model (11)–(12) can be estimated using fitted values from the disaggregate model. Specifically, the aggregate model parameters can be estimated by using the method of moments to fit the covariance structure implied by the aggregate error model to the assumed "true" covariance structure calculated from the disaggregate model parameter estimates.[45] These calculations suggest that, from the perspective of aggregate regions, variation attributable to idiosyncratic shocks in the disaggregate model is simply attributed to region–specific shocks in the aggregate model. For example, estimating the within–U.S. aggregate error model using the covariance matrix fitted from the disaggregate model parameter estimates underlying Table 1 yields innovation variance shares for common, region–specific, and industry–specific shocks of 32.2, 55.3, and 12.5 percent, respectively. Essentially, the common and industry–specific shares are the same as in the "true" disaggregate model estimates, while the region–specific share is the sum of the "true" disaggregate region–specific

[45] When time series on the data are available, GMM estimation of the error model is equivalent to method of moments estimation.

and idiosyncratic shares. Arguably, this outcome is reasonable in that, from the perspective of an aggregate region, idiosyncratic (or region–industry) shocks are disturbances specific to the region.

Overall, comparing the within–U.S. and cross–country estimates of the aggregate VAR/factor model yields conclusions in line with those drawn from the disaggregate model, with one exception. In both the aggregate and disaggregate estimates, region–specific shocks are a larger source of variation in international data than in within–U.S. data, while industry–specific shocks are less important in international variation than in within–U.S. variation (in the quarterly data). The results differ in that the aggregate estimates indicate common shocks are of roughly equal importance within the U.S. and internationally, while the disaggregate estimates indicate common shocks are more important within the U.S. than internationally. The difference in estimates raises some uncertainty about the benchmark conclusion that common shocks are less important internationally than within the U.S., since, if the disaggregate model were "true," the aggregate estimates of common shock shares would be essentially the same as the disaggregate estimates.

While the within–U.S. and cross–country estimates might also be seen as indicating that the shocks affecting nations are much bigger than those affecting U.S. regions, differences in the underlying data preclude making such a comparison. The variance of the overall reduced–form shock to each region, estimated from the model parameters and reported in the second column of each table, is much larger for European nations than for U.S. regions. This overall shock reflects the common, region–specific, and industry–specific components included in the VAR/factor model. Comparing these estimates is problematic because the within–U.S. results are for total employment in a region, while the international results are for industrial production in manufacturing in a nation. The greater volatility in the international data may simply reflect the facts that: (1) the manufacturing industry is more volatile than an overall economy; and (2) industrial production is more volatile than employment, at least in the U.S.

5.2 Alternative identification schemes

Other studies in the literature rely on alternative VAR identifications of shocks that are common, region–specific, etc. Coulson (1993) examines the sources of fluctuations in Philadelphia using a VAR, for each industry i, in the growth rates of total U.S. employment, U.S. employment in industry i, total Philadelphia employment, and Philadelphia employment in industry i. Common, industry i–specific, Philadelphia–specific, and idiosyncratic shocks are identified using a Choleski ordering, augmented by the restriction that a shock to U.S. industry i have no immediate effect on total Philadelphia employment.[46] Coulson and Rushen (1995) use the same basic model to examine fluctuations in Boston industries, with the model augmented to include national defense spending. Coulson and Rushen also investigate the sources of Boston fluctuations with a VAR in the growth rates of U.S. employment, U.S. defense spending, San Jose employment, and Boston employment. They identify common, defense–specific, San Jose–specific, and Boston–specific shocks with a Choleski decomposition, taking the San Jose–specific shock as a proxy for non–defense technological change. Viñals and Jimeno (1996) examine the sources of fluctuations in European unemployment rates with a VAR, for each nation, in EU–wide unemployment and national unemployment.[47] Common and nation–specific shocks are identified with a Choleski decomposition. The same specification is applied to overall and U.S. state unemployment.

The basic models used by Coulson (1993), Coulson and Rushen (1995), and Viñals and Jimeno (1996) can be viewed as restricted versions of the disaggregate or aggregate VAR/factor models. Jimeno (1992) shows that, conditional on certain assumptions, a VAR/factor model in I sectoral growth rates can be aggregated to produce a set of I bivariate VARs in aggregate growth and growth

[46] Coulson and Rushen (1995) justify the same restriction by arguing that a shock to a particular industry should have no immediate effect on total employment in the nation or a metropolitan area.

[47] Viñals and Jimeno (1996) restrict the VAR such that national (or U.S. state) unemployment has no effect on EU (or U.S.) unemployment. They report that imposing this restriction has no effect on the results. Viñals and Jimeno also examine the sources of fluctuations in regions within European nations by adding to the basic model an equation for regional unemployment, assuming that region–specific shocks have no effect on either EU or national unemployment.

in each sector i, with national and sector–specific shocks identified by a Choleski decomposition. The key assumption is that the law of large numbers applies to sector–specific shocks, so that the weighted average of the sector–specific shocks has a variance equal to 0.

These Choleski decomposition–based models yield estimates broadly consistent with the benchmark results. In Coulson and Rushen's (1995) estimates for annual, total Boston employment, common shocks are the leading source of innovation variance, accounting for 56 percent. Region shocks are a smaller, but significant, source of variation. In the Coulson (1993) and Coulson and Rushen (1995) estimates for monthly industry data, idiosyncratic shocks are the leading source of region–industry variation — and, in fact, much more important than in the quarterly benchmark estimates. For example, Coulson's estimates show that, from the perspective of the average one– and two–digit industry in Philadelphia, idiosyncratic shocks account for 90 percent of the innovation variance. In contrast to the benchmark estimates, Coulson and Coulson and Rushen find that common, region–specific, and industry–specific shocks are trivial sources of innovation variance and only modest sources of steady–state variation. In light of section 4's discussion of cross–section and time–series aggregation, this contrast in results is probably largely due to Coulson and Coulson and Rushen's use of monthly data for a metropolitan area, rather than quarterly data for BEA regions.[48] In Viñals and Jimeno's (1996) estimates for annual unemployment, common shocks are less important in Europe than in the U.S., while nation–specific shocks are more important in Europe. For example, averaged across states, the share of innovation variance due to common shocks is 79 percent, compared to an average share of 44 percent for European nations.

5.3 Dynamic factor models

A number of studies in the literature, including Camen (1989), Forni and Reichlin (1997), Gerlach and Klock (1988), Gregory, et. al. (1997), and Lumsdaine and Prasad (1997), use dynamic

[48] Estimation of sets of bivariate VARs in U.S. total growth and regional growth — where the region is either a BEA region or a state — with monthly and quarterly data also supports this conclusion. In these models, as in Coulson (1993) and Coulson and Rushen (1995), common and region–specific shocks were identified using a Choleski decomposition.

factor models to disentangle the sources of fluctuations.[49] Typically, these studies ignore industries and assume fluctuations in region r are driven by unobserved common and region–specific factors that follow autoregressive processes with mutually orthogonal innovations. Using c_t to denote the common factor and $u_{r,t}$ to denote the region r–specific factor, the basic model is

$$X_{r,t} = \delta_r(L)c_t + u_{r,t}, \quad \delta_r(L) = \delta_{r,0} - \delta_{r,1}L - \ \ldots \ \delta_{r,m_\delta}L^{m_\delta} \tag{13}$$

$$\psi(L)c_t = \nu_t, \quad \psi(L) = 1 - \psi_1 L - \ \ldots \ - \psi_{m_\psi}L^{m_\psi} \tag{14}$$

$$\pi_r(L)u_{r,t} = v_{r,t}, \quad \pi(L) = 1 - \pi_1 L - \ \ldots \ - \pi_{m_\pi}L^{m_\pi}. \tag{15}$$

Typically, m_δ is restricted to equal 0, so $\delta_r(L)$ simplifies to just $\delta_{r,0}$.

Compared to a VAR/factor model, the standard dynamic factor model has both advantages and disadvantages. As discussed by Clark (1994), the dynamic factor approach offers the advantage that the dynamics of different types of shocks — for example, common and region–specific shocks — are allowed to differ. In contrast, the VAR/factor model assumes that both common and region–specific shocks are propagated by the same dynamic (VAR) structure. The disadvantage of the dynamic factor approach is that region–specific shocks are not allowed to propagate across regions — all covariation is attributed to common shocks. The VAR/factor model, however, allows region–specific shocks to propagate across regions.

The results of most studies using dynamic factor models are broadly in line with the VAR/factor model results presented in this paper. Camen (1989) and Lumsdaine and Prasad (1997) find evidence of a significant common component in the monthly growth rates of international industrial production.[50] In Gerlach and Klock's (1988) estimates for quarterly GDP growth

[49] Given Forni and Reichlin's (1997) estimation approach, which relies on observable measures of the factors, their analysis could alternatively be classified with the dummy variable or observables studies discussed in Section 6. The Forni and Reichlin study is grouped with other factor model analyses largely because their estimation method forms the factors as *variance–weighted* averages of the observed data. The optimal predictors that could be obtained using the standard state–space representation of the factor model would also be *variance–weighted* averages of the data, making the methods analogous in this respect.

[50] Camen (1989) reports a variance decomposition, but that decomposition appears to be flawed. The model

in the G7 excluding Italy, most variation in each country is due to the country–specific factor (an average of more than 70 percent), although a significant portion (more than 20 percent) is due to the common factor. The Gregory, et. al. (1997) estimates for quarterly growth in GDP, consumption, and investment in the G7 nations show that country–specific components are the leading source of variation.[51] Averaged across countries, the share of steady–state variation in GDP due to country–specific components is 47 percent. The common and idiosyncratic factors are roughly equal in importance, with common shocks, for example, accounting for an average of 28 percent of the variation in GDP. Estimated with H–P filtered data, however, the common factor is roughly equal in importance to country–specific factors, with both accounting for an average of about 45 percent of the steady–state variation in GDP.

While Forni and Reichlin's (1997) findings differ significantly from those reported above, they may do so spuriously. Forni and Reichlin fit dynamic factor models to annual growth in personal income by U.S. counties and to annual growth in GDP by regions within European nations. The U.S. model features common, state, and local components; the European model includes common, national, and local components. In contrast to much of the literature and to the results presented in this paper, Forni and Reichlin's within–U.S. and cross–country variance decompositions are very similar. For the U.S., the common, state, and local components account for an average of 46, 23, and 31 percent of the observed variation.[52] Using a six country sample, the European, national, and local components account for an average of 47, 24, and 29 percent of the observed variation. It seems likely, however, that using comparable disaggregations for within–U.S. and European data

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relates growth to lags 0-2 of common international and European factors (which follow AR(2) processes) and to lags 1-12 of the dependent variable. Camen decomposes variation in each country into components attributable to the international and European factors and to the lagged dependent variables, apparently assuming orthogonality among all sources. Yet the lagged dependent variables should be correlated with the lags of the factors appearing in the equation.

[51] The model includes a common component that affects all variables, country–components that affect all variables in a given country, and idiosyncratic (country–sector) components.

[52] It is not clear whether the reported decompositions represent the average of county or aggregate state estimates. Similarly, it's not clear whether the reported estimates for Europe apply to regions within nations or nations.

would produce results more in line with the standard. Forni and Reichlin's U.S. data, for counties, are far more disaggregate than their European data, which are more like U.S. states. Based on section 4's comparison of results for state and BEA regions, common components are probably much less important in county data than in state data.

Estimates for the data used in this study provide further evidence that the dynamic factor model yields conclusions similar to those obtained with the disaggregate VAR/factor model. In particular, the dynamic factor model estimates, like the benchmark estimates, consistently show common components to be less important and region–specific components to be more important in international data than in within–U.S. data. Estimating a dynamic factor model with quarterly employment growth in the BEA regions produces innovation variance shares, averaged across regions, of 54.3 percent for the common component and 45.7 percent for the region–specific components.[53] Using quarterly growth in European industrial production yields estimated innovation variance shares, averaged across nations, of 17.5 percent for the common component and 82.5 percent for the nation–specific components.

6. Alternative Error Model Approaches

The studies and results reviewed above generally treat the shocks of interest as unobservable and estimate the associated error model with what can be viewed as factor model methods. Many studies in the literature, however, rely on alternative approaches to estimating error models. This section reviews two alternatives: using dummy variables to represent components that are common, region–specific, and so on; and using observed aggregate data to represent common components. In the case of the dummy variable approach, results from existing studies are augmented with new results directly comparable to the benchmark estimates.

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[53] In the estimated model, $m_\delta = 0$, $m_\psi = 4$, and $m_\pi = 4$, and the raw U.S. data span 1947-97. The variance of the shock to the common component is normalized to 1. For each region, the region–specific innovation variance share is formed as the ratio $\mathrm{Var}(v_{r,t})/(\delta_{r,0}^2 + \mathrm{Var}(v_{r,t}))$.

6.1 The dummy variable approach

Many studies, including Bayoumi and Prasad (1997), Bini Smaghi and Vori (1992), Costello (1993), Davis, et. al. (1997), Hooker and Knetter (1997), Marston (1985), Prasad and Thomas (1997), Rosenbloom and Sundstrom (1997), and Stockman (1988), have used regressions on dummy variables to quantify the importance of common, region–specific, and industry–specific components. In this approach, a common factor or shock is represented with a set of dummy variables for time, while region–specific and industry–specific factors are captured with sets of variables interacting the time dummies with region and industry dummies. Pooled data on employment growth in industry i in region r, for example, are then regressed on the dummy variables. The pooled data are often demeaned, allowing different means for each region–industry unit, although authors such as Costello and Stockman instead add region–industry dummies to the model to capture the means. The relative importance of different components is gauged from changes in the regression R^2 associated with adding or dropping a set of dummies. These shares correspond to weighted averages, across the unit of observation, of the shares of variance attributable to each shock.

The treatment of dynamics varies across studies. Many, including Bayoumi and Prasad (1997), Bini Smaghi and Vori (1992), Costello (1993), Stockman (1988), Prasad and Thomas (1997), and Rosenbloom and Sundstrom (1997), simply abstract from dynamics and regress growth rates on dummy variables. Since the annual growth rates used in these analyses are typically only weakly or modestly serially correlated, abstracting from dynamics may be presumed to have small effects. Other studies of annual data, such as Davis, et. al. (1997) and Hooker and Knetter (1997), use lagged dependent variables to capture dynamics, restricting the coefficients to be the same across regions (these studies abstract from industries). Equivalently, Stockman fits the dummy variable model to quarterly residuals from AR processes estimated for each region–industry unit. While not used in the literature, an alternative approach would be to capture dynamics with the restricted VAR structure of (2).

Many researchers use the dummy variable approach primarily because it is, for some specifications, simpler to implement than the unobservables, or factor model, approach.[54] This greater tractability, however, comes with some costs. First, the typical dummy variable regression restricts the response coefficients on common, region–specific, and industry–specific components to be the same across regions and industries. Many researchers allow for some differences in coefficients by normalizing each data series by its sample standard deviation, in which case the effective response coefficients differ across regions according to overall volatility. In contrast, the unobservables model (3) allows for unrestricted coefficients. Second, the dummy variable approach does not readily allow variance decompositions at different levels of aggregation. There is no simple way to use regression estimates based on region–industry data to decompose the sources of variation in aggregate regions. With the unobservables approach, however, decompositions of variance at different levels of aggregation are straightforward. Finally, depending on the treatment of means and on whether the data panel is balanced, the error components may not be orthogonal, complicating the variance decomposition. If mean growth rates are captured by dummy variables to the model or if some region–industry series are missing, some of the variation in the data will be attributed to covariation among the dummies.

The dummy variable studies that report variance decompositions obtain results broadly in line with the VAR/factor model estimates presented in this paper. Using GDP growth rates for one–digit industries in BEA regions, Bayoumi and Prasad (1997) find that the shares of region–industry variance due to common, region–specific, industry–specific, and idiosyncratic components are 29, 19, 25, and 27 percent, respectively. Using one–digit data for eight European nations, Bayoumi and Prasad estimate variance shares of 19, 16, 18, and 47 percent for common, region–specific, industry–specific, and idiosyncratic shocks. In these estimates, as in the benchmark annual results

[54] More generally, the dummy variable method has both advantages and disadvantages compared to the approach of treating the shocks as unobservables. Using dummies to represent shocks corresponds to *fixed effects* methodology, while treating the shocks as unobservables corresponds to estimating the model with *random effects* methodology. Sources such as Judge, et. al. (1985) discuss the merits of these methodologies.

on the sources of region–industry variation, common shocks and industry–specific shocks are less important internationally than within the U.S., while idiosyncratic shocks are more important. Bayoumi and Prasad's results differ from the benchmark only in that region shocks are of roughly equal importance in international and within–U.S. data, rather than of greater importance in international data.[55] This difference may partly reflect the use of the dummy variable approach. In the estimates discussed below, the gap between the cross–country and within–U.S. shares for region–specific shocks is somewhat smaller with the dummy variable model than with the disaggregate VAR/factor model. The difference may also be viewed as partly reflecting sampling uncertainty — with a large number of estimates, some small fraction are bound to differ from the "true" norm.

Using a model that excludes the common component, Bini Smaghi and Vori (1992), Costello (1993), and Stockman (1988) find nation–specific and industry–specific effects to be important sources of international fluctuations. For annual growth in industrial production by manufacturing industries across European nations, Bini Smaghi and Vori estimate that the orthogonal components of nation–specific and industry–specific effects explain 19 and 17 percent, respectively, of nation–industry variation. In annual Solow residuals for two–digit industries in the G7 excluding France, Costello estimates that the orthogonal component of the nation–specific effects accounts for 16 percent of the variation in the average nation–industry unit, while the orthogonal component of industry–specific effects accounts for 18 percent. Using annual growth in industrial production by two–digit industries across eight nations, Stockman attributes 17 and 19 percent of region–industry variation to the orthogonal components of nation–specific and industry–specific effects, respectively. Note that, in these studies, because the mean growth rates are modeled with dummies rather than filtered out, the estimates understate the absolute importance of the nation–specific and industry–specific factors. The understatement occurs because the total sum of squares used in forming the

[55] While this study views Bayoumi and Prasad's (1997) estimates as falling roughly in line with other estimates, the authors view their results as suggesting great similarity in U.S. and international decompositions and as therefore quite unusual.

estimates is boosted by the non–zero mean growth rates that differ across region–industry pairs.

By comparison, Bini Smaghi and Vori (1992) find that, for within–U.S. data, region–specific shocks are much less important than in international data, while industry–specific shocks are much more important in within–U.S. data. Using annual growth in GDP for manufacturing industries within U.S. regions, Bini Smaghi and Vori estimate variance shares of 5 and 58 percent for the orthogonal components of nation–specific and industry–specific effects, respectively. The very large role of industry–specific shocks in the U.S. estimates appears to reflect the absence of a common factor in the model.

Using annual unemployment rates for U.S. states, Davis, et. al. (1997) conclude that both common and region–specific components are important. Allowing the region–specific component to follow an AR(1) process, Davis, et. al. find that regional shocks are persistent. The contrast with estimates based on just the 1970-78 period suggests that Marston's (1985) findings of a much smaller role for region–specific shocks and low persistence of the shocks is largely the result of Marston's short sample. Prasad and Thomas (1997) examine the sources of fluctuations in annual employment in one–digit industries in Canadian provinces. According to their estimates, common, province–specific, and industry–specific shocks each account for about 12–14 percent of region–industry variation, while more than 60 percent of the variation is due to idiosyncratic shocks. Using biennial, Depression–era employment for manufacturing industries in U.S. states, Rosenbloom and Sundstrom (1997) find that common and industry–specific factors explain about 11 and 16 percent, respectively, of region–industry variation. Probably reflecting the use of biennial, rather than annual, data, the orthogonal component of the region–specific effects accounts for only about 2 percent of the variation. Note that, like some of the results discussed above, these estimates understate the absolute importance of the error components because the mean growth rates are modeled in the regression rather than filtered out.

Comparing the disaggregate VAR/factor model estimates to dummy variable estimates for the same data provides further evidence that the approaches yield broadly similar results. Using the annual within–U.S. growth rates underlying the benchmark results reported in Table 3, dummy model estimates indicate that common, region–specific, industry–specific, and idiosyncratic factors account for, respectively, 49.1, 18.1, 21.7, and 11.1 percent of region–industry variation.[56] Using the annual European data underlying Table 4, estimating the dummy model yields corresponding shares of 21.8, 23.5, 13.9, and 40.8 percent. In these results, as in the benchmark annual results, when international estimates are compared to within–U.S. estimates of the sources of annual *region–industry* variation, common and industry–specific shocks are less important, while region–specific and idiosyncratic shocks are more important. As indicated above, however, the difference in the international and within–U.S. importance of region–specific shocks is somewhat smaller than in the disaggregate VAR/factor model results.

6.2 The observables approach

Blanchard and Katz (1990), Decressin and Fatás (1995), and Hess and Shin (1997) quantify the sources of regional variation by using observed aggregate variables to represent common components.[57] More specifically, Blanchard and Katz and Decressin and Fatás regress a regional variable on a contemporaneous aggregate variable — for example, employment growth in state r is regressed on U.S. employment growth. They use the resulting $\bar{R}^2$ to measure the importance of aggregate forces, and $1 - \bar{R}^2$ to quantify the importance of region–specific factors. Analyzing within–U.S. data, Hess and Shin (1997) decompose the variation in state–industry GDP and productivity into common, industry–specific, region–specific, and idiosyncratic portions using observable measures of the components constructed from aggregates of the data. The observables

[56] Each region–industry series is demeaned and normalized by its sample standard deviation prior to the regression estimation.

[57] Eichengreen (1993) and Ramey (1996) can be viewed as following the same approach. Eichengreen regresses the log of regional unemployment on the log of national unemployment. Eichengreen does not, however, attempt to use the regression R^2's to quantify the relative importance of common and region–specific factors, and the trends in the data, which refer to workers rather than rates, rule out doing so. In commenting on Shea (1996), Ramey regresses annual growth in city–industry employment on dummies that capture city–specific shocks and national growth in the industry, which is viewed as an observable measure of the common component. Ramey finds that the vast majority of city–industry variation is idiosyncratic.

approach can be justified by appealing to the law of large numbers.[58] For example, aggregated across a large number of regions, region–specific shocks should have no effect on an aggregate variable. The aggregate variable, therefore, reflects just the common factor and can then be used as a proxy for the common component.

Shea's (1996) analysis of the sources of comovement among industries located within a city can also be viewed as an observables approach. In Shea's model, city–industry employment growth is a function of national, city–specific, industry–specific, and city–industry forces.[59] As noted by Ramey (1996), Shea links these forces to observable variables. National shocks, for example, are represented with the price of oil and a monetary policy indicator, specified as an interest rate spread. The variation in city–industry employment due to city–industry shocks is linked to observable measures of interindustry linkages, such as an input–output matrix.

Some other studies not directly interested in quantifying the relative importance of common and region–specific factors — Carlino and DeFina (1995) and Samolyk (1994) — can also be viewed as fitting in the observables class.[60] In these analyses, the dependent variables are regional growth rates relative to the aggregate U.S. growth rate. Using a VAR in the annual growth rates of personal income in BEA regions relative to the nation, Carlino and DeFina find that region–specific shocks propagate across regions. In the steady state, own–region shocks account for an average of 39 percent of relative growth rate variance, with shocks to other regions accounting for the remaining 61 percent. Regressing relative annual growth rates for personal income in U.S. Census Regions

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[58] The Choleski decomposition–based VARs developed by Jimeno (1992) and used by Coulson (1993), Coulson and Rushen (1995), and Viñals and Jimeno (1996) can also be viewed as observables models. In a bivariate model without dynamics, for example, the Choleski decomposition identifies the common component as the national variable and the sector–specific component as the residual from a regression of sectoral growth on contemporaneous national growth. Jimeno's results therefore provide formal justification for the observables approach, although, as typically applied, the observables approach abstracts from the dynamics built into Jimeno's analysis.

[59] Technically, the only shocks in Shea's model are national and city–industry shocks. One set of city–industry shocks, however, serves to capture city–specific and industry–specific shocks through the covariance structure of the city–industry shocks. What Shea refers to as the *asymmetric local spillover (or CITY)* contribution corresponds to an industry–specific component. What Shea labels the *local common shock (or COMMON)* contribution represents the city–specific effect.

[60] Samolyk's (1994) model also includes time dummies designed to capture common effects, but presumably in only the credit variables that appear as regressands.

on various measures of regional banking conditions, Samolyk concludes that there is evidence of a regional credit channel.

The variance decompositions available from studies using the observables approach are broadly consistent with results obtained using other approaches. For annual employment growth in U.S. states, Blanchard and Katz (1992) report an average $\bar{R}^2$ of 66 percent, indicating that most annual variation is due to a national component and a smaller, but significant, portion is due to a region–specific component. Decressin and Fatás (1995) find that regressing employment growth for some small European countries and for regions in France, Germany, Italy, Spain, and the U.K. on growth for all of Europe yields an average $\bar{R}^2$ of just 20 percent. Adding nation–specific effects to the model boosts the average $\bar{R}^2$ to 50 percent. They conclude that a smaller proportion of movements in employment growth is common to European regions than to U.S. states. Hess and Shin's (1997) estimates indicate that nearly three–quarters of the variation in annual state–industry GDP is idiosyncratic, while most of the rest is industry–specific. Shea's (1996) results show that aggregate shocks are the leading source of variation at the city–industry level, accounting for an average of 43 percent. Idiosyncratic shocks are second in importance, accounting for 35 percent. Industry–specific and city–specific forces are much less important, with shares of 14 and 6 percent, respectively.[61]

7. Other Approaches to Quantifying Sources of Comovement

While most of the literature relies on the approaches reviewed above, a significant portion uses other approaches to examining the sources of fluctuations within and across countries. Some studies use correlations across regions and industries to gauge the relative importance of common, region–specific, and industry–specific factors. Others seek to identify structural economic shocks. This section reviews these alternative approaches.[62]

[61] The reported figures do not add to 100 percent because a small fraction, 2 percent, is due to interaction terms.

[62] The review omits some studies that rely on still other approaches to quantifying sources of comovement, since general comparisons of the sources of within–country and cross–country fluctuations are difficult to make from this research. These studies include Engle and Kozicki (1993), Sill (1997), Filardo and Gordon (1994), Quah (1994, 1996), and Selover and Jensen (1996).

7.1 Correlation analyses

Many studies use cross–region and cross–industry correlations to examine the relative importance of common, region–specific, and industry–specific shocks. Christodulakis, et. al. (1995), Fatás (1997), Ghosh and Wolf (1997), Hess and Shin (1998), Kollman (1995), and Wynne and Koo (1997) rely exclusively on correlations in gauging the sources of fluctuations.[63] Altonji and Ham (1990), Bini Smaghi and Vori (1992), Clark (1998), Costello (1993), Helg, et. al. (1995), and Hess and Shin (1997), studies principally reliant on other approaches and discussed in previous sections, also use correlations to assess the sources of comovement. With the exception of Clark (1998), Engle and Kozicki (1993), and Helg, et. al. (1995), which rely on quarterly data, these correlation analyses all use annual data.

As indicated by the simple model (1), the covariances between industries i and j in region r and between regions r and s for industry i are

$$\mathrm{Cov}(e_{r,i,t}, e_{r,j,t}) = \mathrm{Var}(c_t) + \mathrm{Var}(u_{r,t}) \tag{16}$$

$$\mathrm{Cov}(e_{r,i,t}, e_{s,i,t}) = \mathrm{Var}(c_t) + \mathrm{Var}(n_{i,t}). \tag{17}$$

The cross–industry covariance $\mathrm{Cov}(e_{r,i,t}, e_{r,j,t})$ will be bigger than the cross–region covariance $\mathrm{Cov}(e_{r,i,t}, e_{s,i,t})$ if the variance of the region–specific shock $u_{r,t}$ is bigger than the variance of the industry–specific shock $n_{i,t}$. Correlations across aggregate regions also provide some measure of the importance of common and region–specific factors. Some caution is required in interpreting the correlations, however, because as indicated by the aggregate model (11), covariances across aggregate regions are determined by both the common factor and by industry–specific factors. Therefore, correlations across aggregate regions reflect the importance of not only common and region–specific factors but also industry–specific factors.

[63] Gerlach (1988) uses coherences, the frequency domain analog of correlations, to examine comovement in international industrial production. The coherences reveal significant comovement at business cycle frequencies. Gerlach's study is not included in the discussion because there is no corresponding analysis of within–country coherences.

The results from correlation analyses are generally consistent with the model–based results discussed in sections 3–6. Using data for industries within countries, Costello (1993), Helg, et. al. (1995), and Kollman (1995) find that growth is more correlated across industries within a country than across countries within an industry, suggesting that nation–specific factors are more important than industry–specific factors. Using data for industries in U.S. regions, Ghosh and Wolf (1997) and Kollman find that growth is more correlated across regions within an industry than across industries within a region, indicating that, at the region–industry level, industry–specific shocks are a more important source of variation than region–specific factors are.

Moreover, when industries are ignored, correlations across regions within a country are generally greater than correlations across countries, suggesting region–specific factors are more important in international fluctuations than in within–country fluctuations. In Wynne and Koo (1997), the average correlation of GSP across U.S. regions corresponding to districts of the Federal Reserve System is .79, while the average correlation of GDP across EU countries is .29. Hess and Shin (1997) report similar findings. The estimates of Fatás (1997) indicate that correlations are greater for regions within European nations than across nations. The cross–country correlations reported by Christodulakis, et. al. (1995), Costello (1993), and Engle and Kozicki (1993) and within–country correlations reported by Altonji and Ham (1990), Clark (1998), Ghosh and Wolf (1997), Hess and Shin (1998), and Kollman (1995) are consistent with these results. In one exception to the general pattern, Bini Smaghi and Vori (1992) find that correlations of GDP are greater across European countries than across U.S. regions. Bini Smaghi and Vori's result might be an artifact of their use of linearly detrended data rather than growth rates or data detrended with a moving average filter.

7.2 Models of structural economic shocks

The studies reviewed in sections 3–6 seek to simply decompose fluctuations into common, region–specific, and industry–specific components without formally identifying more structural sources of those components.[64] The components are typically just qualitatively interpreted along the lines discussed in section 2, with common shocks, for example, viewed as representing similar changes in monetary policy, fiscal policy, or technology. Some studies, however, seek to identify structural economic shocks and their role in fluctuations within and across countries.

Bayoumi and Eichengreen (1992) first use a structural VAR for a given region to estimate aggregate supply and demand shocks and then assess the cross–region comovement of the structural shocks. For annual data on GDP and the price level, Bayoumi and Eichengreen use a version of Blanchard and Quah's (1989) structural VAR to identify aggregate supply and demand shocks for BEA regions and European nations. In this identification, the supply shocks correspond to disturbances having permanent effects on the level of output and prices, and the demand shocks correspond to disturbances having a permanent effect on the price level but not the level of output. After estimating models for each region separately, Bayoumi and Eichengreen assess the comovement of the structural shocks with correlations and principal component analysis.

Chamie, et. al. (1994) extend the Bayoumi and Eichengreen (1992) approach to incorporate monetary policy disturbances. Chamie, et. al. use a variant of Blanchard and Quah's (1989) structural VAR to estimate aggregate supply, real demand, and monetary policy shocks. The model is estimated with quarterly data on industrial production, the consumer price level, and M1 in the U.S. Census Regions and European countries. The sources of comovement in the shocks are than quantified by fitting the factor model (9) to, separately, supply, real demand, and monetary policy shocks.

Ahmed, et. al. (1993) and Kwark (1996) use even more structural frameworks based on two–country, open economy, dynamic general equilibrium models. Ahmed, et. al. use a structural VAR

[64] Norrbin and Schlagenhauf (1988) use a DYMIMIC model approach to link the common, region–specific, and industry–specific components to structural forces. Particularly, the components are related to, respectively, monetary and fiscal policy, weather variables, and Solow residuals. The specification of these variables, however, does not determine the identification of the common, region–specific, and industry–specific components. Rather, it only serves to potentially yield more efficient estimates. In contrast, the studies discussed in this section use particular identifications to obtain certain structural shocks.

imposing only long–run restrictions to identify a worldwide technology shock, country–specific labor supply shocks, and relative fiscal policy, monetary policy, and preference shocks. Kwark imposes both long–run and short–run restrictions on a VAR to identify a worldwide technology shock and country–specific technology shocks. In each analysis, the full set of shocks is estimated using a single model containing series for two economies. More specifically, the models are estimated using quarterly data for the U.S. versus the rest of the G7 (Ahmed, et. al. exclude Italy).

The results from these more structural studies are consistent with those of the literature surveyed above, in that region–specific shocks are more important in cross–country fluctuations than in within–country fluctuations. Bayoumi and Eichengreen's (1992) estimates indicate that aggregate supply and demand shocks are significantly more idiosyncratic across European nations than across US regions, suggesting a smaller region–specific component in disturbances to U.S. regions than to European nations. The estimates of Chamie, et. al. (1994) for supply, real demand, and monetary policy shocks also show region–specific components are more important in European nations than in U.S. regions, although, as noted in Section 4.3, their measures of U.S. production are not truly regional and lead to underestimates of the importance of region–specific components. Ahmed, et. al. (1993) find that, while the world shock is important, own country–specific supply shocks originating in the labor market are the leading source of output fluctuations. Specifically, the world technology shock and the U.S.–specific labor supply shock account for about 20 and 70 percent, respectively, of the variation in U.S. output growth. Similarly, Kwark's (1996) results show that output fluctuations are primarily due to own country–specific technology shocks.

8. A Summary of the Literature and Implications for the Role of Borders in Business Cycles

As the preceding review has indicated, the literature on the sources of business cycle fluctuations within and across countries offers many estimates of the importance of common, region–specific, and industry–specific components.[65] Tables 9 and 10 summarize the estimates in the

[65] Idiosyncratic shocks are excluded from the discussion for two reasons. First, researchers are generally less

literature, with Table 9 presenting innovation variance share estimates and Table 10 reporting steady–state share estimates. Overall, the evidence suggests three broad conclusions on the sources of business cycle fluctuations within and across countries.

First, common shocks are less important in international fluctuations than in within–country fluctuations. This result is robust across most modeling approaches and data specifications, with two notable exceptions.[66] One is that the aggregate VAR/factor model estimates reported in this paper indicate common shocks are of roughly equal importance internationally and within the U.S. As indicated in Section 5.1, the exception evident in the aggregate model estimates may be viewed as raising some uncertainty about this first conclusion. The second exception is Forni and Reichlin's (1997) analysis, in which common shocks are of roughly equal importance in cross–country and within–country data. As discussed in Section 5.3, however, this result seems to be an artifact of the different degrees of regional aggregation used for the U.S. and Europe.

A second broad conclusion suggested by the literature is that region–specific shocks are more important in international fluctuations than in within–country fluctuations. This result, too, is robust across most specifications, with only two exceptions. One is Bayoumi and Prasad's (1997) dummy variable analysis, which yields roughly equal international and within–U.S. roles for region–specific shocks at the region–industry level. As discussed in section 6.1, this exception partly reflects the model used and may also be viewed, given the considerable evidence in favor of the benchmark conclusion, as partly reflecting sampling uncertainty in the estimates. The other exception is Forni and Reichlin (1997), in which region–specific shocks are of roughly equal importance in cross–country and within–country data. Again, however, their result is probably an artifact of the

interested in the role of region–industry shocks than in the roles of common, region–specific, and industry–specific shocks. Indeed, many analyses in the literature do not include idiosyncratic shocks. Second, estimates of the importance of idiosyncratic shocks vary widely across specifications.

[66] The estimates of Coulson (1993) and Coulson and Rushen (1995) are also contrary to the general pattern. Their estimates for industries in Philadelphia and Boston, respectively, produce small variance shares for common shocks in monthly data. However, their low estimates are probably attributable to the use of relatively disaggregate data.

different degrees of regional aggregation used.

The third and final conclusion evident from the literature is that industry–specific shocks, when measured most accurately, are less important internationally than within the U.S.[67] As indicated in sections 4.1 and 4.2, industry–specific shocks would seem to be most accurately measured in quarterly (or monthly) data, with the within–U.S. regions used in the comparison defined as aggregates, such as the BEA regions, comparable in size to the countries considered. However, when measured less accurately, the relative importance of industry–specific shocks often differs from the benchmark. If quarterly U.S. estimates are based on states rather than BEA regions, industry–specific shocks are of roughly equal importance internationally and within the U.S. Moreover, in annual data, from the aggregate region perspective industry–specific shocks are more important in international fluctuations than in within–U.S. fluctuations.

Prima facie, these findings suggest that lowering the economic borders dividing nations should reduce the relative importance of country–specific disturbances in international fluctuations, while boosting the importance of common and industry–specific factors. In this simple view, lowering borders should make national economies more integrated, causing international business cycle fluctuations to look more like within–country fluctuations. This simple view is supported by Frankel and Rose (1997, 1998), who find that the cross–country bilateral correlation of business cycle activity is strongly and positively related to the degree of bilateral trade intensity.[68] More careful consideration, however, suggests that the extent to which lowering borders causes international fluctuations to more closely resemble within–country fluctuations depends on two general issues. First, in what sense and by how much are borders lowered? Second, what are the structural sources

[67] The estimates of Coulson (1993) and Coulson and Rushen (1995) may be viewed as contrary to this pattern, since they find that industry shocks are only small sources of region–industry variation in Philadelphia and Boston, respectively. However, their relatively low estimates are probably attributable to the use of relatively disaggregate data.

[68] Further corroborating the simple view, Fatás (1997) finds that cross–Europe correlations of employment growth are higher in the EMS period than in a period preceding the EMS. However, the increases in correlations are probably too small to be statistically significant, especially given than the pre–EMS and EMS periods are each only 14 years long.

of the measured common and nation–specific shocks?

To date, the economic borders dividing nations are more substantial than the borders separating regions within nations. Different nations generally determine monetary and fiscal policies independently, although, as noted below, policies such as a fixed exchange rate regime will lead to some coordination of policy. Nations also restrict migration and, to a lesser degree, trade and capital flows. Other features such as language and general cultural differences also pose economic borders. Overall labor mobility, for example, is likely to be lower between regions with different languages than between regions with a common language. In contrast, regions within a nation, such as U.S. states, typically determine local fiscal policies but are affected by national monetary and fiscal policy. Moreover, regions within a nation allow free migration and essentially unrestricted flows of trade and capital. Cultural differences are typically minor, with U.S. regions, at least, sharing a common language.

Whether and how much lowering borders among nations affects the features of international fluctuations depends on how borders are lowered. Agreements that focus on just reducing trade barriers are likely to have modest effects on the features of fluctuations, since the agreements do not seek to coordinate monetary and fiscal policies or increase labor flows. Common currency agreements, such as the EMU, should have more substantial effects. EMU will of course produce a coordinated monetary policy and impose some restrictions on fiscal policy by limiting the allowable deficit–to–GDP and debt–to–GDP ratios. Some expect that EMU will lead to increased flows of labor, capital, and goods and, in turn, to implicit coordination of tax policy (see, for example, Bayoumi and Eichengreen (1993)). However, economic borders among EMU–member nations will likely remain considerably greater than those among, say, U.S. regions, because the agreement does not create an EMU–wide fiscal authority and cultural differences will limit labor mobility. With these stronger borders among nations, nation–specific shocks should continue to be a greater source of variation internationally than region–specific shocks are in the U.S. The federal tax and transfer system in the U.S., for example, significantly mitigates the effects of region–specific shocks, so reducing the importance of nation–specific shocks in Europe to the level of region–specific shocks in the U.S. would require a common fiscal authority in Europe (see Sala–i–Martin and Sachs (1992), for instance).

An assessment of how lowering borders will affect the features of international fluctuations also hinges on the interpretation of the shocks estimated from historical data. In part, the assessment depends on whether the monetary and fiscal policies of different countries are viewed as having been largely coordinated. For example, the monetary policies of many countries have sometimes been linked by fixed exchange rate policies. To some extent, then, estimates of the role of common factors in international fluctuations already reflect common monetary policy. If policies have been largely common, at least in the data used to form estimates, lowering borders through monetary union will not have much effect on the international importance of common shocks and, by extension, region–specific and industry–specific shocks.

As noted by Fatás (1997), the assessment of borders also partly depends on whether monetary and fiscal policy are viewed as historically important sources of variation and on policy's perceived stabilization capabilities. If, as argued by Christodulakis, et. al. (1995), policies have been important sources of nation–specific shocks, coordinating policies through an agreement like EMU should boost the importance of common shocks and reduce the role of nation–specific disturbances. The role of common shocks is especially likely to rise if policy has very limited stabilization capabilities. Suppose, however, that policy shocks have been small but the systematic component of policy has been important for business cycle stabilization. Under this interpretation, coordinating policy won't reduce the importance of nation–specific shocks and may in fact exacerbate nation–specific fluctuations, since each nation will be giving up the ability to respond to the significant shocks hitting its economy. This interpretation underlies the commonly–cited view that, if nation–specific shocks are a major source of variation, monetary union is not desirable (see Bayoumi and Eichengreen (1993), for example). Note, however, that as Bini Smaghi and Vori (1992) and Frankel and Rose (1997, 1998) argue, the suitability of a group of regions for currency union is endogenous. Adopting a common currency will likely change the relative importance of common and region–specific shocks and thereby alter the suitability of a region for currency union.

Ultimately, weighing all these considerations, it seems likely that the *prima facie* conclusion is roughly right. Lowering economic borders should increase the integration of nations, thereby modestly raising the relative importance of common and industry–specific factors in international fluctuations and lowering the importance of country–specific disturbances. However, the sources of international fluctuations are likely to remain considerably different from the sources of within–U.S. fluctuations because the borders among nations will remain greater than the borders among U.S. regions. In addition, there is some uncertainty about the qualitative effects of lowering borders. If the measured nation–specific shocks largely reflect non–policy forces and national policies have an important stabilization role, adopting common policies and giving up the right to conduct independent stabilization policies may not alter much the importance of nation–specific shocks.

9. Conclusions

Drawing on a recent literature, this paper examines the evidence on the sources of business cycles within and across countries and the implications for the importance of borders in business cycles. Estimates of a benchmark econometric model are used to organize a review of the literature. The benchmark model and estimates provide a foundation for discussing alternative data specifications and data issues, variations on the baseline model, and still other approaches to quantifying sources of comovement. Along many dimensions, the paper examines the robustness of the benchmark results.

Overall, the results reviewed in this paper yield three general conclusions on the sources of fluctuations within and across countries. First, common shocks account for a smaller share of variation in international data than in within–country data. Second, region–specific shocks are more important in international fluctuations than in within–country fluctuations. Finally, industry–specific shocks, measured accurately, are a smaller source of variation internationally than within countries. These findings suggest that reducing the economic borders dividing nations should lower the importance of country–specific disturbances in international fluctuations, while raising the importance of common and industry–specific factors. Admittedly, however, the effects may be modest and are qualitatively uncertain.

Appendix 1: G7 Results

Table A1.1 **Variance Decomposition** **Quarterly Disaggregate VAR/Factor Model Estimates, 1976:2-97:1** **G7 Industrial Production, Two–Digit Manufacturing Industries**										
	Fitted	Shares of Innovation Variance				Fitted	Shares of Steady–State Variance			
	Innov. Var.	Common	Reg.	Ind.	Idiosyn.	St. St. Var.	Common	Reg.	Ind.	Idiosyn.
Region–Industry Level										
Avg. reg.-ind.	93.628	.092	.313	.103	.491	124.382	.097	.357	.099	.447
Region Level										
Canada	44.451	.028	.713	.019	.239	70.049	.032	.695	.021	.253
France	29.745	.293	.486	.103	.118	35.559	.253	.522	.094	.131
W. Germany	52.500	.231	.402	.100	.267	65.815	.202	.418	.099	.281
Italy	64.380	.043	.746	.048	.163	76.090	.059	.729	.047	.165
Japan	17.561	.008	.499	.003	.490	36.213	.060	.508	.029	.402
U.K.	32.443	.062	.599	.029	.310	38.277	.068	.585	.038	.309
U.S.	22.089	.056	.794	.006	.143	31.244	.052	.780	.012	.156
Average	37.596	.103	.606	.044	.247	50.464	.104	.605	.048	.242

Notes: See the notes to Table 2.

Table A1.2 **Variance Decomposition** **Annual Disaggregate VAR/Factor Model Estimates, 1972-93** **G7 Employment, One–Digit Industries**					
	Fitted	Shares of Innovation Variance			
	Innov. Var.	Common	Region	Industry	Idiosyn.
Region–Industry Level					
Average reg.-ind.	9.387	.167	.299	.198	.337
Region Level					
Canada	4.447	.048	.711	.054	.187
France	.272	.099	.391	.075	.435
W. Germany	1.200	.033	.585	.026	.356
Italy	.407	.015	.270	.557	.157
U.K.	2.221	.348	.458	.071	.122
U.S.	3.214	.539	.408	.003	.050
Average	1.960	.180	.471	.131	.218

Notes: See the notes to Table 4.

Table A1.3 Variance Decomposition Annual Disaggregate VAR/Factor Model Estimates, 1977-96 G7 Industrial Production, Two–Digit Manufacturing Industries					
	Fitted	Shares of Innovation Variance			
	Innov. Var.	Common	Region	Industry	Idiosyn.
Region–Industry Level					
Average reg.-ind.	19.720	.212	.397	.119	.272
Region Level					
Canada	26.109	.380	.567	.009	.044
France	3.913	.454	.428	.073	.045
W. Germany	6.840	.238	.635	.055	.072
Italy	9.733	.080	.816	.007	.096
Japan	12.043	.148	.601	.022	.230
U.K.	7.474	.173	.706	.103	.018
U.S.	9.613	.474	.458	.015	.053
Average	10.818	.278	.602	.040	.080

Notes: See the notes to Table 6.

Table A1.4 Variance Decomposition Quarterly Aggregate VAR/Factor Model Estimates, 1976:2-97:1 G7 Industrial Production, Two–Digit Manufacturing Industries								
	Fitted	Shares of Innovation Variance			Fitted	Shares of Steady–State Variance		
	Innov. Var.	Common (s.e.)	Reg. (s.e.)	Ind. (s.e.)	St. St. Var.	Common	Region	Industry
Canada	33.234	.518 (.124)	.447 (.121)	.035 (.011)	75.976	.388	.413	.198
France	20.414	.244 (.095)	.696 (.095)	.060 (.016)	44.772	.133	.648	.219
W. Germany	44.501	.016 (.031)	.938 (.036)	.046 (.015)	71.064	.028	.779	.193
Italy	43.655	.075 (.061)	.899 (.060)	.025 (.007)	87.071	.088	.697	.215
Japan	16.254	.008 (.020)	.870 (.040)	.122 (.039)	39.820	.128	.616	.257
U.K.	18.905	.141 (.105)	.794 (.106)	.065 (.021)	45.733	.140	.508	.352
U.S.	16.237	.642 (.098)	.268 (.084)	.090 (.034)	35.148	.476	.322	.203
Average	27.600	.235 (.039)	.702 (.038)	.063 (.019)	57.083	.197	.569	.234

Notes: See the notes to Table 8.

Appendix 2: Data

1. U.S. employment

Monthly payroll employment data by state, national industry, and for industries within states were taken from the Bureau of Labor Statistic's Internet site. Because seasonally adjusted state data from the BLS do not begin until 1983, all state series were obtained in unadjusted form and then adjusted using the X–11 filter. The seasonally adjusted state data were then aggregated into the eight BEA regions, defined below. The regions used differ from the BEA definitions, however, in that Alaska and Hawaii are excluded from the Far West because data for those states begin substantially later than data for other states. The seasonally adjusted data were converted to the quarterly frequency by averaging within each quarter.

The data on total employment for the continental U.S. states, the District of Columbia, and U.S. industries span the period 1947:Q1 to 1997:Q4. But for some industry–state series, the data are available for a much shorter sample. Consequently, the employment shares needed in some of the results are based on the period 1982-97, over which all series are available. In addition, in the estimation of disaggregate models, the data begin in 1956 rather than 1947, and the measure of employment in a given region–industry pair simply excludes, for the entire sample, states with missing data. For example, because the available series on construction employment in Connecticut begins in only 1982, the measure of construction employment in New England used in the disaggregate analysis simply excludes Connecticut.[69]

Most of the U.S. analysis relies on employment in the eight SIC one–digit industries listed below. However, aggregate models for employment in 19 two–digit manufacturing industries, listed below, are also estimated. One industry, tobacco, is excluded from the two–digit analysis because the industry is almost entirely based in the Southeast region, making it difficult to distinguish a

[69] However, Connecticut is not excluded from other series on industry employment in New England, except in those cases for which Connecticut data are missing.

shock to tobacco from a shock to the Southeast. Because many series on state employment in two–digit industries are missing, the shares needed to estimate the aggregate VAR/factor model with two–digit data are calculated using annual, 1982-94 GSP for industries in BEA regions. The real GSP data were obtained from the Regional Economic Information System CD–ROM.

BEA regions

New England: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
Mideast: Delaware, District of Columbia, Maryland, New Jersey, New York, Pennsylvania
Great Lakes: Illinois, Indiana, Michigan, Ohio, Wisconsin
Plains: Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
Southeast: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia
Southwest: Arizona, New Mexico, Oklahoma, and Texas
Rocky Mountain: Colorado, Idaho, Montana, Utah, Wyoming
Far West: Alaska, California, Hawaii, Nevada, Oregon, Washington

Note: The analysis of employment excludes Alaska and Hawaii from the Far West region.

SIC one–digit industries

Mining
Construction
Manufacturing
Transportation and public utilities
Wholesale and retail trade
Finance, insurance, and real estate
Services
Government

Note: The analysis of annual within–U.S. data designed to be comparable to analysis of international employment data omits (1) mining and (2) transportation and public utilities.

SIC two–digit manufacturing industries

Lumber and wood products
Furniture and fixtures
Stone, clay, and glass products
Primary metals
Fabricated metals
Industrial machinery and equipment
Electronic and other electrical equipment
Transportation equipment
Instruments and related products
Miscellaneous
Food and kindred products
Textile mill products
Apparel and other textile products
Paper and allied products
Printing and publishing
Chemicals and allied products
Petroleum and coal products
Rubber and misc. plastic products
Leather and leather products

2. International industrial production

Monthly seasonally unadjusted data on industrial production for manufacturing industries within countries were taken from the OECD's Main Economic Indicators database, accessed through DRI. For some country–industry pairs, data early in the sample are available on a quarterly, rather than monthly, basis. Accordingly, the data were converted to the quarterly frequency by averaging monthly observations prior to seasonally adjustment with the X–11 filter. For the purposes of testing stability over time, quarterly, seasonally adjusted data on total industrial production were taken from the IFS database.[70] The 10 European countries, the G7 countries, and the eight ISIC two–digit manufacturing industries used in the analysis are listed below.[71] The European and G7 raw data span 1975:Q3-97:Q1 and 1975:Q1-97:Q1, respectively. The weights needed for the analysis were calculated using figures reported in OECD (1997). These figures include the weights each country gives industries in forming its measure of overall industrial production and the weights used in forming series for production by OECD–industry pairs. The OECD formed the latter weights using 1990 value added, expressed in purchasing power parities, by industries within countries.

European nations

Austria	Italy
Finland	Netherlands
France	Spain
West Germany	Sweden
Ireland	United Kingdom

G7 nations

Canada	Japan
France	United Kingdom

[70] Seasonally adjusted data on total production in Austria, however, were taken from the OECD's Main Economic Indicators database, accessed through DRI.

[71] Countries with any industry data completely missing or available over a period shorter than 1975-97 were excluded from analysis.

West Germany
Italy
United States

ISIC two–digit manufacturing industries

Food, beverages, and tobacco
Textiles, clothing, and footwear
Wood and wood products
Paper and paper products
Chemicals and associated products
Non–metallic mineral products
Basic metals
Metal products, machinery, and equipment

3. International employment and GDP

Annual 1970-93 data on the number of employees and value added (GDP) by country and industry were taken from the OECD's International Sectoral Database. The countries and industries are listed below. The industries generally correspond to ISIC one–digit industries and two–digit manufacturing industries. However, to make the data comparable to the within–U.S. employment series, ISIC one–digit industries (1) transport, storage, and communication and (2) electricity, gas, and water are combined to form an industry corresponding to the U.S. industry transportation and public utilities (following Bayoumi and Prasad (1997)). The set of two–digit industries differs from that used in the industrial production analysis in that wood and wood products is excluded but other manufacturing is included. The weights used in the international analysis were formed as average 1970-93 shares, based on sums of employment or GDP (in PPP terms).

European nations

Belgium
Denmark
Finland
France
West Germany
Italy
Sweden
United Kingdom

G6 nations

Canada
France
West Germany
Italy
United Kingdom
United States

One digit industries

Construction
Manufacturing
Transport, storage, and communication; and Electricity, gas, and water
Wholesale and retail trade, restaurants, and hotels
Community, social, and personal services
Producers of government services

Appendix 3: Treatment of the Adding–Up Condition in the Aggregate VAR/Factor Model

In principle, the full set of regions and industries should not be used in estimation of the aggregate VAR/factor model.[72] Because the sum (or weighted average) across all the regions should equal the sum (or weighted average) across all industries, the full system will, in principle, have a singularity. With unweighted GMM used to estimate the model parameters, the collinearity should not be a problem for obtaining consistent parameter estimates, but would be a problem for obtaining appropriate standard errors and conducting inference. Therefore, in principle, one variable should be dropped from the model. Note, however, that the sector–specific shock variance associated with the dropped variable would remain a parameter to be estimated in the model, because the parameter enters the covariances among the other variables in the model.

In practice, however, the full set of regions and industries is used in the within–U.S. analysis. Two factors prevent the full U.S. model from having a singularity — and, empirically, make the covariance matrix for the full set of growth rates clearly nonsingular.[73] One is that the relevant government agencies derive estimates of regional (state) employment separately from estimates of national employment, with the result that the sum of region employment is not equal to national employment.[74] National employment is, however, constructed to be the sum of national industry employment levels. The second factor is that, even if the data were constructed to sum up in employment *levels*, the growth rates would not be perfect linear combinations. The aggregate growth rates are time–varying weighted averages of disaggregate growth rates, rather than fixed–weighted averages. Based on the same reasoning, Clark (1998) includes all variables in the estimating the

[72] In principle, the same applies to Blanchard and Katz (1992), Carlino and DeFina (1995), and Samolyk (1994). In these studies, the dependent variables are region growth rates relative to national growth. In principle (but not in practice, for the reasons give below), a weighted average of the full set of relative growth rates will equal 0.

[73] Using eigen values normalized following the practice described by Belsley, et. al. (1980), the condition numbers for the covariance matrix of employment growth rates and the covariance matrix of VAR residuals are 16.253 and 8.275, respectively. These condition numbers are below the threshold at which Belsley, et. al. view collinearity as a problem. Dropping a variable from the model produces similar condition numbers.

[74] As noted in various BLS sources, state employment is estimated from the set of state firms sampled as part of the national Establishment Survey program. The BLS constructs U.S. industry and total employment data to estimate national employment from the full set of firms sampled across the 50 states.

aggregate model. However, Kuttner and Sbordone (1997) drop a variable because they construct their region (New York and the U.S. less New York) and industry employment series to sum to national employment.

Nonetheless, the presented within–U.S. results are robust to omitting a variable. Dropping a variable has little effect on the estimates, except that the variance of the shock specific to the omitted variable tends to rise. Loosely speaking, omitting some variable x from the estimation problem has this effect because the variance and covariances of x are important for pinning down the variance of the shock specific to x. When x is omitted, the variance of the shock specific to x becomes a free parameter used to improve the fit of covariances among other variables. The limited sensitivity of the estimates to dropping a variable appears to be importantly related to the non–singularity of the within–U.S. data. Some additional analysis not presented indicates that, when the data are truly singular or nearly singular, dropping a variable has only very small effects on all of the parameter estimates.

In the international analysis, a variable is dropped from the aggregate model estimation. In the international case, the data are constructed as fixed–weight averages of the disaggregate (nation–industry) growth rates. Therefore, by construction, a linear combination of the aggregate national growth rates equals a linear combination of the aggregate industry growth rates. The dropped variable is the growth rate for the metal products industry.

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Table 1 Variance Decomposition Quarterly Disaggregate VAR/Factor Model Estimates, 1957:2-97:4 Within–U.S. Employment, One–Digit Industries										
	Fitted Innov. Var.	Shares of Innovation Variance				Fitted St. St. Var.	Shares of Steady–State Variance			
		Common	Region	Industry	Idiosyn.		Common	Reg.	Ind.	Idiosyn.
Region–Industry Level										
Avg. reg.-ind.	49.727	.130 (.014)	.126 (.007)	.253 (.010)	.491 (.010)	65.285	.170	.159	.286	.384
Region Level										
New England	1.760	.213 (.060)	.276 (.059)	.173 (.030)	.338 (.044)	9.836	.134	.336	.167	.364
Mideast	1.355	.355 (.069)	.345 (.055)	.143 (.024)	.157 (.023)	2.857	.370	.267	.217	.147
Great Lakes	2.869	.586 (.061)	.096 (.037)	.100 (.025)	.218 (.034)	6.436	.544	.099	.202	.155
Plains	1.308	.352 (.068)	.249 (.057)	.149 (.026)	.250 (.032)	3.278	.424	.171	.224	.181
Southeast	1.620	.382 (.066)	.275 (.051)	.206 (.030)	.137 (.020)	4.327	.352	.246	.258	.145
Southwest	1.603	.194 (.061)	.449 (.058)	.076 (.015)	.280 (.038)	4.687	.185	.408	.137	.270
Rocky Mtn.	2.442	.191 (.064)	.466 (.061)	.088 (.016)	.255 (.030)	5.012	.213	.389	.168	.230
Far West	2.249	.304 (.064)	.417 (.059)	.068 (.014)	.211 (.026)	5.470	.292	.347	.162	.199
Average	1.901	.322 (.038)	.322 (.023)	.125 (.012)	.231 (.015)	5.238	.314	.283	.192	.211

Notes: The table reports estimates of the disaggregate VAR/factor model equations (2)–(3) obtained from quarterly growth in one–digit industries in BEA regions. The reported share figures are shares of variance attributable to common, region–specific, industry–specific, and idiosyncratic shocks. The innovation estimates correspond to a decomposition of 1–step ahead forecast error variances. The steady–state estimates are based on a decomposition of 251–step ahead forecast error variances, evaluated using the restricted VAR (7)–(8) written in companion form. The *average reg.-ind.* row reports the average, across region–industry units, of the decompositions for each region–industry unit. As described in section 3.1, the *region level* estimates are based on an aggregation of the fitted variance–covariance matrix of the set of region–industry units. Average 1982-97 employment shares are used as weights in the aggregation. The figures in parentheses are approximate standard errors, calculated with Monte Carlo simulations.

	Fitted Innov. Var.	Shares of Innovation Variance				Fitted St. St. Var.	Shares of Steady–State Variance			
		Common	Region	Industry	Idiosyn.		Common	Reg.	Ind.	Idiosyn.
Region–Industry Level										
Avg. reg.-ind.	151.797	.077	.226	.107	.590	200.060	.080	.252	.129	.538
Region Level										
Austria	29.299	.353	.002	.032	.613	41.837	.279	.083	.069	.569
Finland	55.318	.005	.612	.027	.355	65.553	.028	.582	.049	.341
France	22.029	.214	.390	.216	.181	32.395	.163	.447	.195	.195
W. Germany	50.428	.231	.373	.092	.303	64.053	.198	.403	.092	.307
Ireland	85.070	.000	.568	.006	.425	96.665	.005	.535	.040	.420
Italy	52.602	.001	.745	.081	.172	63.576	.047	.685	.090	.178
Netherlands	26.401	.105	.484	.047	.364	42.833	.078	.475	.084	.362
Spain	44.536	.162	.510	.012	.316	59.369	.137	.480	.037	.346
Sweden	72.933	.231	.285	.014	.470	87.637	.210	.299	.029	.462
United Kingdom	29.715	.004	.668	.029	.300	38.318	.041	.602	.065	.292
Average	46.833	.131	.464	.056	.350	59.224	.119	.459	.075	.347

Table 2
Variance Decomposition
Quarterly Disaggregate VAR/Factor Model Estimates, 1976:4-97:1
European Industrial Production, Two–Digit Manufacturing Industries

Notes: The table reports estimates of the disaggregate VAR/factor model equations (2)–(3) obtained from quarterly growth in two–digit manufacturing industries in the listed countries. The reported share figures are shares of variance attributable to common, region–specific, industry–specific, and idiosyncratic shocks. For simplicity, *region* is used to refer to *nation*. The innovation estimates correspond to a decomposition of 1–step ahead forecast error variances. The steady–state estimates are based on a decomposition of 251–step ahead forecast error variances, evaluated using the restricted VAR (7)–(8) written in companion form. The *average reg.-ind.* row reports the average, across region–industry units, of the decompositions for each region–industry unit. As described in section 3.1, the *region level* estimates are based on an aggregation of the fitted variance–covariance matrix of the set of region–industry units. The fixed weights used in the aggregation are taken from OECD (1997).

Table 3
Variance Decomposition
Annual Disaggregate VAR/Factor Model Estimates, 1972-93
Within–U.S. Employment, One–Digit Industries

	Fitted	Shares of Innovation Variance			
	Innov. Var.	Common	Region	Industry	Idiosyn.
Region–Industry Level					
Average reg.-ind.	9.232	.426	.152	.266	.155
Region Level					
New England	2.615	.576	.294	.059	.071
Mideast	1.418	.751	.137	.055	.057
Great Lakes	2.968	.825	.131	.023	.020
Plains	2.195	.781	.160	.042	.017
Southeast	2.845	.783	.149	.063	.005
Southwest	2.945	.603	.341	.027	.029
Rocky Mtn.	2.567	.578	.360	.033	.029
Far West	2.268	.826	.061	.068	.044
Average	2.478	.715	.204	.046	.034

Notes: The table reports estimates of the disaggregate VAR/factor model equations (2)–(3) obtained from annual growth in one–digit industries in BEA regions. For comparability to cross–country results for annual employment growth, two industries — (1) mining and (2) finance, insurance, and real estate — are excluded from the estimation. In contrast, Table 1's results for quarterly data are based on the full set of one–digit industries. For additional details, see the notes to Table 1.

Table 4
Variance Decomposition
Annual Disaggregate VAR/Factor Model Estimates, 1972-93
European Employment, One–Digit Industries

	Fitted	Shares of Innovation Variance			
	Innov. Var.	Common	Region	Industry	Idiosyn.
		Region–Industry Level			
Average reg.-ind.	5.044	.136	.282	.182	.400
		Region Level			
Belgium	.867	.277	.148	.203	.371
Denmark	.856	.017	.214	.701	.069
Finland	.335	.249	.635	.034	.082
France	2.453	.128	.545	.114	.213
W. Germany	1.152	.144	.357	.243	.257
Italy	.547	.404	.221	.159	.216
Sweden	1.529	.342	.428	.070	.160
United Kingdom	3.301	.359	.384	.017	.240
Average	1.380	.240	.366	.193	.201

Notes: The table reports estimates of the disaggregate VAR/factor model equations (2)–(3) obtained from annual growth in one–digit industries in the listed countries. For simplicity, *region* is used to refer to *nation*. The *region level* estimates are obtained by aggregating the region–industry estimates using average 1970-93 employment shares. For additional details, see the notes to Table 1.

Table 5
Variance Decomposition
Annual Disaggregate VAR/Factor Model Estimates, 1958-97
Within–U.S. Employment, One–Digit Industries

	Fitted	Shares of Innovation Variance			
	Innov. Var.	Common	Region	Industry	Idiosyn.
		Region–Industry Level			
Average reg.-ind.	9.659	.350	.129	.303	.219
		Region Level			
New England	1.914	.590	.208	.093	.108
Mideast	1.544	.773	.115	.088	.024
Great Lakes	3.291	.788	.093	.087	.032
Plains	1.635	.727	.147	.095	.031
Southeast	2.100	.709	.159	.115	.017
Southwest	2.440	.564	.338	.058	.040
Rocky Mtn.	1.894	.440	.413	.084	.063
Far West	2.626	.751	.140	.052	.057
Average	2.181	.668	.202	.084	.047

Notes: The table reports estimates of the disaggregate VAR/factor model equations (2)–(3) obtained from annual growth in one–digit industries in BEA regions. For comparability to Table 1's quarterly results, data over the full sample and all industries are included in the estimation, in contrast to the annual, international data–comparable estimates reported in Table 3. For additional details, see the notes to Table 1.

Table 6
Variance Decomposition
Annual Disaggregate VAR/Factor Model Estimates, 1978-96
European Industrial Production, Two–Digit Manufacturing Industries

	Fitted	Shares of Innovation Variance			
	Innov. Var.	Common	Region	Industry	Idiosyn.
Region–Industry Level					
Average reg.-ind.	20.619	.216	.255	.199	.330
Region Level					
Austria	6.693	.317	.380	.059	.244
Finland	12.652	.253	.477	.042	.228
France	5.100	.565	.261	.136	.038
W. Germany	9.240	.379	.280	.171	.170
Ireland	25.238	.224	.410	.028	.338
Italy	6.854	.446	.367	.045	.142
Netherlands	3.665	.611	.182	.131	.076
Spain	10.674	.374	.410	.062	.154
Sweden	14.108	.549	.145	.033	.272
United Kingdom	7.807	.040	.798	.146	.015
Average	10.203	.376	.371	.085	.168

Notes: The table reports estimates of the disaggregate VAR/factor model equations (2)–(3) obtained from annual growth in two–digit manufacturing industries in the listed countries. For additional details, see the notes to Table 2.

Table 7
Variance Decomposition
Quarterly Aggregate VAR/Factor Model Estimates, 1948:2-97:4
Within–U.S. Employment, One–Digit Industries

	Fitted Innov. Var.	Shares of Innovation Variance Common (s.e.)	Region (s.e.)	Industry (s.e.)	Fitted St. St. Var.	Shares of Steady–State Variance Common	Region	Industry
New England	2.454	.038 (.057)	.770 (.052)	.192 (.031)	11.952	.053	.553	.394
Mideast	1.346	.771 (.271)	-.055 (.269)	.284 (.046)	7.051	.196	.403	.401
Great Lakes	3.333	.209 (.133)	.629 (.121)	.162 (.022)	18.168	.096	.522	.382
Plains	1.299	.112 (.094)	.559 (.077)	.329 (.048)	7.030	.069	.534	.396
Southeast	1.329	.443 (.125)	.202 (.108)	.355 (.061)	9.098	.139	.467	.393
Southwest	1.259	.035 (.050)	.621 (.038)	.345 (.067)	8.022	.017	.671	.312
Rocky Mtn.	2.454	.146 (.106)	.695 (.093)	.160 (.024)	8.976	.074	.681	.244
Far West	3.060	.103 (.085)	.765 (.076)	.132 (.022)	11.042	.075	.621	.304
Average	2.067	.232 (.067)	.523 (.047)	.245 (.031)	10.167	.090	.557	.353

Notes: The table reports estimates of the aggregate VAR/factor model (10)–(12) obtained from quarterly growth in total employment in BEA regions and U.S. one–digit industries. The reported share figures are shares of variance attributable to common, region–specific, and industry–specific shocks. The innovation estimates correspond to a decomposition of 1–step ahead forecast error variances. The steady–state estimates are based on a decomposition of 251–step ahead forecast error variances, evaluated using the VAR written in companion form. The weights needed for model estimation are fixed at average 1982-97 employment shares.

Table 8
Variance Decomposition
Quarterly Aggregate VAR/Factor Model Estimates, 1976:4-97:1
European Industrial Production, Two–Digit Manufacturing Industries

	Fitted Innov. Var.	Shares of Innovation Variance Common (s.e.)	Region (s.e.)	Industry (s.e.)	Fitted St. St. Var.	Shares of Steady–State Variance Common	Region	Industry
Austria	26.305	.385 (.111)	.572 (.103)	.044 (.020)	50.932	.232	.537	.231
Finland	33.571	.006 (.017)	.967 (.020)	.027 (.010)	67.834	.028	.823	.148
France	15.271	.313 (.093)	.622 (.088)	.065 (.029)	41.201	.179	.510	.311
W. Germany	35.938	.244 (.121)	.722 (.114)	.034 (.026)	66.484	.183	.678	.139
Ireland	56.146	.032 (.041)	.952 (.042)	.016 (.010)	100.259	.032	.766	.202
Italy	32.624	.011 (.028)	.960 (.031)	.029 (.012)	77.501	.081	.731	.187
Netherlands	21.539	.469 (.117)	.491 (.112)	.040 (.018)	47.885	.252	.516	.232
Spain	29.116	.172 (.122)	.800 (.118)	.028 (.013)	70.493	.123	.734	.143
Sweden	49.877	.365 (.114)	.613 (.113)	.023 (.015)	108.934	.183	.586	.231
United Kingdom	18.779	.080 (.058)	.872 (.058)	.048 (.025)	39.528	.057	.722	.221
Average	31.917	.208 (.045)	.757 (.041)	.035 (.017)	67.105	.135	.660	.205

Notes: The table reports estimates of the aggregate VAR/factor model (10)–(12) obtained from quarterly growth in manufacturing production in the listed countries and in "world" two–digit industry aggregates, where "world" is defined to consist of just the listed countries. The reported share figures are shares of variance attributable to common, region–specific (or nation–specific), and industry–specific shocks. The innovation estimates correspond to a decomposition of 1–step ahead forecast error variances. The steady–state estimates are based on a decomposition of 251–step ahead forecast error variances, evaluated using the VAR written in companion form. The weights needed for model estimation are fixed at the weights reported in OECD (1997).